

EXAMINING THE EFFICACY OF ATTENDANCE AS A PREDICTOR OF
ACADEMIC PERFORMANCE

A Dissertation

Presented to

The Faculty of the Department of Educational Leadership
Sam Houston State University

In Partial Fulfillment
of the Requirements for the Degree of
Doctor of Education

by

Andrew Patrick Miller

December, 2019

EXAMINING THE EFFICACY OF ATTENDANCE AS A PREDICTOR OF
ACADEMIC PERFORMANCE

by

Andrew Patrick Miller

APPROVED:

Susan Skidmore, PhD
Committee Chair

D. Patrick Saxon, EdD
Committee Member

Nara Martirosyan, EdD
Committee Member

Stacey L. Edmonson, EdD
Dean, College of Education

DEDICATION

This dissertation is dedicated to my family, first and foremost my wife—Lauren, and my children—Elizabeth, Gabriel, Mara, and Jeremy. You are the loves of my life and the chief motivation for me even beginning this undertaking. I love you and hope you “try something challenging and learn something new” each and every day.

This is further dedicated to those students who are underperforming because of the choices they have made up to this point as well as the academic advisors, coaches, and mentors who intervene to help at-risk students change their decision-making paradigms, reshaping the trajectories of their academic careers.

ABSTRACT

Miller, Andrew P., *Examining the efficacy of attendance as a predictor of academic success*. Doctor of Education (Developmental Education Administration), September 2019, Sam Houston State University, Huntsville, Texas.

Recognizing that attendance is the most prescient indicator of student academic performance (Crede, Roch, & Kieszczynka, 2010), it would seem only logical that researchers would attempt to pin-point when absenteeism becomes a measurable deterrent to student success. The purpose of this study is to examine the extent to which cumulative absences at specific points in the semester (Weeks 4, 8, 12, and 16) affect final course outcome at one small-to-mid-sized, private, religiously affiliated 4-year university in the Midwest United States. A quantitative non-experimental design was employed to answer this question, as well as to explain the extent to which that impact is mitigated by the number of credits and the number of weekly class sessions for a given course. The target population for this study was a convenience sampling of students enrolled in traditional undergraduate courses during the Fall and Spring semesters for academic years 2016-2019.

Research questions one through four explored the relationship between cumulative absences at given time intervals (i.e., weeks 4, 8, 12, and 16) and final course outcome (i.e., final grade and pass rate). Each accumulated absence, up to a certain threshold, corresponded with a drop in the pass rate ranging from a 6% when measured at Week 4 to 2% when measured at Week 16. Similarly, the per absence decrease in final grade average ranged from -.2 at Week 4 to -.08 at Week 16.

The results of this study were not as strongly correlated as prior research (e.g., Crede, Roch, & Kieszczynka, 2010) and suggest other factors must also be considered to

best inform the intervention of student success personnel. As a general principle however, the impact of absenteeism is largely detrimental to students' success. This message should not only be shared frequently with students, but also heavily emphasized with faculty. Administrators trying serve an increasingly diverse student body with an ever-decreasing budget while also seeking a balance between academic freedom and accountability would be wise to support the development of an attendance-informed early alert system.

KEY WORDS: Attendance, Absenteeism, Academic success analytics, Early-alert intervention.

ACKNOWLEDGEMENTS

There are so many people who have helped me get to this point, to whom I owe a heartfelt thank you and a drink—or several—for their support, encouragement, and assistance throughout my academic journey. First, my wife, Lauren, thank you for your trust in me. When I first came to you with this idea, you were supportive and have remained every bit encouraging as you were from the onset. The sacrifices you have made to help me accomplish this milestone certainly matched, and at times exceeded, my own throughout this pursuit. We started this journey with two kids and that number doubled throughout my studies, it would not have been possible without your love, support, and hard work. Thank you, my love!

To my children—Elizabeth, Gabriel, Mara, and Jeremy—thank you for the motivation and encouragement you have provided me. You sacrificed in this as well. Although I missed some opportunities for playing, you still found time to snuggle with me while I read or insisted on sitting on my lap to help me write. For those times where you had to be patient, quiet, and well behaved for Mom, I am forever grateful.

Thank you, Mom and Dad – for teaching me the discipline and work ethic to accomplish something as unanticipated as this. You provided me a solid foundation and love for learning, you instilled a firm understanding that academics come first, and challenged me to think critically and consider diverse perspectives on any topic I was entertaining at that moment. For those lessons as well as the science fair projects and assignments where you helped me overcome my chronic procrastination, thank you.

To my SHSU family, most notably my dissertation chair—Dr. Skidmore—thank you for your encouragement, mentorship, and relentless attention to detail. You were

always quick with returning revisions and helped take my mess of unorganized thoughts and formulate a coherent thesis. My committee members, Drs. Saxon and Martirosyan, thank you for all the time you put into reading and revising my work, for your comments and encouragement throughout the past year, and your tutelage throughout my time in the program. This has been an incredibly rewarding experience, in large part due to the tremendous instruction from you three and the SHSU faculty.

To Cohort 5 – I am grateful for each of you. Your continued affirmation and encouragement helped me overcome my self-doubts. Your partnership on projects, Facebook group reminders for upcoming assignments, and our Zoom meetings helped carry me through. Thank you for your trust and willingness to be vulnerable each semester, as it affirmed me that I was not alone in the stresses of this major undertaking. You have my utmost respect and admiration – continue making a tremendous difference in your students’ lives; you have left an indelible mark on mine.

To my Lord and Savior, Jesus Christ. Thank you for filling me with the resolve and clarity to pursue this degree. I still do, and forever will, recall vividly that night I was praying to you, asking what your will for me was and for a sign as to what my next life decision would be—football or something else. While praying the Rosary, specifically the Joyful Mysteries, you introduced this idea of pursuing my doctorate and filled me with the confidence to know this is what I was meant to do. With each mystery, it became more and more clear. For speaking to me that evening, walking alongside me throughout this journey, and placing these wonderful people in my life, thank you. All things truly are possible through you—please bless me and help me to use this degree and the lessons I have learned to do your will; to serve you through my service to others.

TABLE OF CONTENTS

DEDICATION	iii
ABSTRACT.....	iv
ACKNOWLEDGMENTS	vi
TABLE OF CONTENTS.....	viii
LIST OF TABLES	xii
CHAPTER I: INTRODUCTION.....	1
Statement of the Problem.....	1
Theoretical Framework.....	2
Purpose of the Study	6
Scholarly Significance	7
Definition of Terms	8
Delimitations.....	8
Limitations	9
Threats to Validity	10
Organization of this Study	14
CHAPTER II: REVIEW OF LITERATURE	15
Is the Success of Students Important?	18
What Constitutes Student Success?	20
What Impacts Student Success? Where are the Gaps in Knowledge?	24
Instructional Delivery Modalities	27
Brief History of Recording Attendance	34
Is Attendance Meaningful for Student Success?	37

If Attendance is Meaningful, Why is Absenteeism so Prevalent?.....	48
If Attendance is Consequential, but Viewed as Optional, Why Not Mandate it?	57
CHAPTER III: METHOD	69
Research Questions.....	70
Design Overview	71
Data Source.....	72
Characteristics of Traditional Undergrad Courses at the Research Site.....	73
Procedure	74
Analysis	75
CHAPTER IV: RESULTS.....	79
Research Questions.....	79
Hypothesis	80
Data Source and Demographics.....	81
Research Question 1	85
Research Question 2	88
Research Question 3	91
Research Question 4	94
Research Question 5	97
Research Question 6	99
Research Question 7	100
Research Question 8	102
Conclusion	104
CHAPTER V: DISCUSSION.....	106

Implications	114
Limitations	117
Direction for Further Research	118
Summary.....	119
REFERENCES	121
APPENDIX.....	133
VITA	135

LIST OF TABLES

Table	Page
1 Threats to internal validity	12
2 Threats to external validity	13
3 Participant Characteristics	83
4 Number of Participants Enrolled by Course Characteristics	84
5 Participants' Grade Distribution Across All Courses.....	85
6 Week 4 Absences Descriptives	86
7 Week 4 Absences and Final Course Grade Correlations by Credits and Sessions Per Week.....	87
8 Week 8 Absences Descriptives	89
9 Week 8 Absences and Final Course Grade Correlations by Credits and Sessions Per Week.....	90
10 Week 12 Absences Descriptives	92
11 Week 12 Absences and Final Grade Correlations by Credits and Sessions per Week	93
12 Week 16 Absences Descriptives	95
13 Week 16 Absences and Final Grade Correlations by Credits and Sessions per Week	96
14 Week 4 Correlations Between Absences and Final Grade & Course Outcome by Class Standing.....	99
15 Week 8 Correlations Between Absences and Final Grade & Course Outcome Correlations by Class Standing.....	100

16	Week 12 Correlations Between Absences and Final Course Grade & Course	
	Outcome Correlations by Class Standing	102
17	Week 16 Correlations Between Absences and Final Course Grade & Outcome	
	Correlations by Class Standing	104

CHAPTER I

INTRODUCTION

The perception of import of class attendance in student success is anecdotally ubiquitous; most everyone acknowledges, or perhaps assumes, that in order to succeed in a course one must attend that course regularly. Institutional attendance policies, as well as classroom policies, demonstrate the regularity with which this notion manifests. Although faculty and administrators demonstrate a penchant for researched based decision- and policy-making, the theory that reinforces these actions is “seldom stated or reviewed critically” (Astin, 1984, p. 520). Assumptions about attendance may help explain the limited literature examining the predictive impact class attendance has on student performance metrics, like course grade, term to term retention, year to year retention, etc. That which is published however, underscores the complexity of the relationship between attendance and student success. In fact, the very notion of class attendance, or absenteeism for that matter, unlocks a litany of ethical, practical, and policy questions.

Statement of the Problem

Faculty and students, alike, seemingly and almost intuitively acknowledge the importance of attending class. This intuition has strong theoretical underpinnings, rooted deeply in theories of engagement (Astin, 1984) and learning (Donovan & Radosevich, 1999). Although literature throughout the past century has often supported this notion (i.e., Lukkarinen, Koivukangas, & Seppälä, 2016; Turner, 1927), policies and practice seem to operate primarily based upon assumptions for when absenteeism becomes detrimental. This is evidenced by inconsistent thresholds for chronic absenteeism in

school policy and the lack of a common understanding of when absences tangibly inhibit student success. Recognizing that attendance is the most prescient indicator of student academic performance (Crede, Roch, & Kieszczynka, 2010), it seems only logical that the efforts of student success professionals and researchers would begin to focus on pinpointing when absenteeism becomes a deterrent to student performance, most notably grades and retention.

Although it is true that researchers have proposed a *70% Rule* (Colby, 2004) and others have used this research to assert 20% [the 80% Rule] as the trigger for intervention (Newman-Ford et al., 2008), both of these studies examined absences summatively, comparing student aggregate absences to final grade. There is a dearth of literature seeking to identify when cumulative absences become problematic, in a formative metric. Consequently, faculty and student affairs professionals are often unsure of when, specifically, to intervene. A formative measure of attendance risk on course outcome may perhaps provide the just-in-time data academic success professionals need to curb attendance risk. To date, no such literature could be found. The salience of attendance in the context of student success is such that faculty and staff ought to be operating from more than a simple and nondescript assumption.

Theoretical Framework

According to Astin (1984) “The amount of student learning and personal development associated with any educational program is directly proportional to the quality and quantity of student involvement in that program” (p. 519). Attendance provides one such quantitative measure for student involvement. Critics argue, however, that quantity of attendance is less relevant if students are only *physically* attending class

and not also *mentally* engaged (St. Clair, 1999). If a student is texting, napping, or otherwise distracted, a stated attendance policy may be effective in getting a student to attend, but “cannot compel them to pay attention to the material nor to engage in the learning experience” (Groce, Willis, Sonner, & James, 2012; p. 129). Thus, critics argue attendance may not necessarily be an effective predictor of class success. Furthermore, traditional lectures are not the only means by which learning can, or does, occur. The proliferation of online classes, internships, and co-curricular learning are but a few examples of learning that transpires outside of the traditional lecture, arguably undermining the impetus for in-class attendance.

Even if attendance may not be a reliable predictor of academic success, the practice of not attending class—*absenteeism*—may be a predictor for academic risk. Crede, Roch, and Kieszczynka (2010) suggested that students who are chronically absent from class are more apt to engage in massed practice, the act of binge learning. They cited Donovan and Radosevich (1999) who found a difference in performance of nearly half a standard deviation lower for those who engaged in massed practice as opposed to distributed practice—the act of distributing learning material more frequently, over longer periods of time. Additionally, a lack of attendance may indicate lower academic motivation, thereby negatively impacting student grades. Thus, Durden and Ellis (2003) argued that attendance actually serves as a proxy for student success, because it represents the manifestation of academic motivation. The causality dilemma of attendance, motivation, and performance exacerbates and obfuscates the competing theories, both formal and informal, that guide policies on attendance.

In an attempt to resolve this paradox, Crede et al. (2010) synthesized the evidence depicting the relationship between class attendance, student characteristics (i.e., academic motivation, control, discipline, cognitive ability), and class performance for college students. They tested four competing models for the relationship between these factors: (a) the *mediated effects model*, whereby individual differences in student characteristics impact student attendance, which subsequently affects course performance; (b) the *unique effects model* where student characteristics and attendance “exert largely unique effects” (p. 275) on course performance; (c) the *common cause model* where attendance and grades are both influenced by the same student characteristics; and (d) the *bidirectional model* where performance serves as either a motivator or demotivator for further attendance.

Based upon their results, Crede et al. (2010) identified the unique effects model as the prevailing depiction of the relationship between these factors, whereby the relationship between attendance and academic success is largely unaffected by motivation and vice-versa. Their conclusion was based on the following three findings: “(a) attendance is strongly related to grades, (b) attendance is only weakly to moderately related to student characteristics, and (c) a mandatory attendance policy has a (small) positive effect on average grades” (p. 285). This finding is important, insofar that attendance was a stronger predictor than characteristics like high school grade point average, standardized test scores, and study behavior, which underscores the salience of attendance for students, irrespective of academic aptitude. Crede et al. (2010) postulated this may, in part, be a product of the design and instructional methods, where faculty plausibly drew more exam questions from lecture than out of class activities. Regardless,

these findings have expounding implications for administrators and instructors seeking to increase student success.

It is with that concept in mind that the conversation shifts from *if* attendance is a predictor of success, to *how* can colleges compel students to attend more regularly. Some argue it is not the role of the institution to mandate any academic behavior. As undergraduate students, they too are scholars, and thus subject to many of the same academic freedom rights and responsibilities as graduate students and faculty (Macfarlane, 2013). If, for example, a student can gain the requisite information and that learning is manifested on graded assignments and exams, then participation points for attendance appear to be a violation of that student's academic freedom rights. Proponents of punitive policy-driven solutions cite accountability measures for publicly funded schools as the justification for compulsory attendance policies (Macfarlane, 2013). Researchers suggest however, that the acknowledgement and emphasis of the importance and relevance of attendance can curb student absenteeism (Corbin, Burns, & Chrzanowski, 2010; Moore, 2006). Thus, attendance behavior could be positively remedied without jeopardizing traditional neoliberal values and academic freedom.

This acknowledgement and emphasis transcends the classroom, with myriad support services augmenting student success. A growing trend with student success initiatives has been the integration of early alert systems; a system of communication that informs personnel of risk factors early enough in a semester for staff to proactively intervene. As Hudson (2005) noted, an early alert system enhances communication between faculty, advisors, and students. Furthermore, this communication leads to more appropriate action taken to best serve the student and their needs. An early alert system

that could gather and disseminate attendance concerns for individual students, at the appropriate time, would provide an opportunity for just in time advisement. This pays dividends in both the short- and long-term successes of students. Not only does an early alert system affect course pass rates, it provides the mechanism for mitigating disruptive behavior (absenteeism), remediating chronic absenteeism, and facilitates reentry to the classroom (Hudson, 2005). The challenge becomes identifying when absenteeism reaches a problematic level, so faculty, advisors, and student success personnel can appropriately intervene with the student to address barriers to the student's success.

Purpose of the Study

The purpose of this study is to identify timely indicators of academic risk due to absenteeism. Whereas research pointing to the 80% Rule as a precise trigger for intervening has examined this threshold as a summative measure, the relationship between cumulative attendance at weeks 4, 8, 12, and 16 of the semester and final course outcome has not previously been explored. Building upon contemporary literature, the objective of the present study was to design and conduct a non-experimental quantitative study to ascertain the moments and thresholds whereby absenteeism becomes an undeniable risk to student success. The data set for this study, by design, was also more robust than most studies found in contemporary literature, as it drew upon data taken over the course of three academic years, spanning every program and class standing at one private, Christian, mid-sized University in the northern Midwest. Although broad in its scope, this breadth was intentional, as it sought to inform academic administrators and instructors on a common set of standards for attendance policies.

Scholarly Significance

The results of this study have a wide breadth of implications for higher education, most notably administrators, faculty, and academic success professionals-moreover students themselves. Any information gleaned from this study could plausibly support and spur subsequent research on classroom engagement and the fundamental design of course curricula. Furthermore, student success professionals can leverage this information and design specific intervention strategies to increase student attendance, ultimately enhancing student performance and retention.

For administrators, institution-wide policies which outline specific consequences for chronic absenteeism can be more precisely written; informed by empirical evidence as opposed to a pervasive, albeit ostensibly correct, assumption about the import of regular classroom attendance. Faculty and instructors, as well as academic success personnel, can leverage this data when designing individual course attendance policies. They can also share this information with their students, emphasizing the critical nature of class attendance with their students. Although some caution and discretion should be exercised when conveying the thresholds for success to students, this information has been shown to be quite effective for enhancing student engagement (Moore, 2005). Furthermore, academic success professionals (i.e., academic advisors, academic coaches, etc.) can use this information to design early-alert warning systems to measure and report on student academic risk. The implication here is that once these professionals have this timely information, they can subsequently intervene with students before the students' absenteeism becomes irreversibly problematic. All these policies and implications speak to the desire to assist students in their pursuit of their educational aspirations, ultimately

leading to higher retention, degree completion, and a higher quality learning experience for students.

Definition of Terms

Although likely intuitive, it is imperative that readers of this study are clear on the operational definition of terms used within this study. Henceforth:

Absenteeism describes the act of not attending a face-to-face class. Generally, this implies the behavior is rather infrequent (Newman-Ford, Fitzgibbons, Lloyd, & Thomas, 2008). Conversely, *Chronic Absenteeism* refers to the pattern of behavior whereby a student is more frequently absent (Newman-Ford et al., 2008). It is understood that those definitions are loosely defined; the necessity for more specificity within these terms is what led to this study. *Attendance* may refer to either the singular act of attending class, as well as the pattern of behavior for regularly attending class. These terms and their use throughout this study align with the literature which informed this study.

Delimitations

The data used within this study were collected from one small-to-mid-sized, private, Christian university located in the northern Midwest. Additionally, these data include only those students enrolled in traditional undergraduate courses during the Fall and Spring semesters for academic years 2015-2018, the only years in which attendance has been recorded in the student information system (Banner). In this context, *traditional* refers to the modality of the courses and not the student population. For the University, traditional represents face-to-face courses offered Monday through Friday and spanning a 16-week semester; students generally enroll in multiple course concurrently. This is contrasted with the *accelerated* format of undergraduate courses where students enroll in

one class at a time and study the same amount of content as traditional courses, but spanning a period of six or eight weeks. Consequently, the generalizability of these results may be rather limited. Further, these data were delimited to students whose attendance rate was greater than 50% of the completed course. Similarly, those course enrollments where a student whose present:absent ratio was less than 2:1 (meaning a student who missed more than 33% of class) and whose final grade was above the Mean population (3.38) were also removed. These two samples of students represent extreme outliers in student behavior and were therefore removed from consideration. Lastly, 1- and 2-credit courses that only lasted half of the semester were removed from consideration. Given the shorter duration, students would not have the same amount of time to either suffer from the ‘compounding impact’ of absenteeism (Chen & Lin, 2008) nor receive the full opportunity for intervention and remediation as full-semester students (Arnold, 2010).

Limitations

The purpose of this study was to identify the thresholds for when cumulative absences have a tangible and substantial impact on final course outcome. Certainly, predicting student success in a course is complex and dependent upon a plethora of factors, including demographic, cognitive, and affective characteristics (Crede, Roch, & Kieszczynka, 2010). Because this study focused on students’ rate of attendance, most of those other factors have been excluded which limits the overall understanding of how these myriad factors interact to impact student performance. Furthermore, because this study drew data solely pertaining to students enrolled in traditional undergraduate, fact-to-face courses, these findings may not be germane to educational offerings falling

outside of these bounds (hybrid and online courses). Perhaps most importantly, the design of the student information system records only the attendance for which faculty input and is thus subject to human error. This is noteworthy insofar that the simple act of faculty recording attendance was shown to positively impact student attendance and subsequently performance (Shimoff & Catania, 2001). Hence, it is plausible that those courses for which faculty did not report attendance, may have higher rates of absenteeism and lower overall student performance. In short, the convenience sample of this study is likely biased towards students who have a greater penchant for attending class, due to the fact that faculty recorded attendance.

As with attendance, student grades are recorded within the student information system based upon the input of the instructor. As Sadler (2009) notes, “grades are typically taken at face value, their integrity being presumed rather than tested” (p. 808). Not only could human error in recording impact the validity of attendance records, so too could errors or the discrepancies in subjective grading practices undermine the integrity of this relationship.

Threats to Validity

Issues of internal and external validity are of the utmost importance to quantitative research methodologists (Onwuegbuzie, 2000). As such, the myriad threats to both internal and external validity must be accounted for to ensure the robustness of the results as a standalone study (credibility), and to encourage replication externally (generalizability).

Threats to internal validity. Creswell (2014) defined threats to internal validity as experimental procedures which “threaten the researcher’s ability to draw correct

inferences from the data” (p. 174). Campbell and Stanley (2015) offer up more than a dozen various threats to the internal validity of quantitative research. Of those, four were acknowledged within this study (Table 1): mortality, history, maturation, and researcher bias.

The first three threats can be attributed to the longitudinal nature of this study. By their very nature of accumulating higher quantities of credits, upperclassmen have shown a propensity for successful course completion; underclassmen have not, necessarily. This simple fact threatened the internal validity in three distinct ways. First *mortality*—the loss of students from a study. Because underperformance contributes to student attrition (e.g., academic dismissal, loss of financial aid, etc.), the inclusion of upperclassmen suggests a potential bias towards those who are retained. Certainly attrition is not solely predicated upon achievement, but students who persist could not have done so without performing at least adequately. Second is *history*—when extraneous events occur during the course of the study that may confound the results of one or more students. Insofar that lived experiences for one student differ from one semester to the next, contextual factors of student success unaccounted for in this study, like hours worked, participation in extra-curricular activities, familial factors, and changes in academic program, may have confounded the data for each student. Third is *maturation*, whereby upperclassmen have refined their skills and strategies for learning. Theoretically, some could have developed strategies to overcome chronic absenteeism potentially rendering one or more absences less consequential than for underclassmen. Interpreting the data from seniors essentially the same as data from freshmen, is inherently biased. It was therefore necessary to examine and analyze the relationship across each of the various class standings.

Researcher bias was also a potential threat, insofar that the collection, cleaning, and analysis of the data may have been predisposed to the sentiments of the researcher. Where decisions needed to be made for removing or manipulating rows of data, to maintain the integrity of the data, any predisposition may have unintentionally biased the data. To account for this, the researcher not only identified the criteria for eliminating data, but also acknowledged those decisions within the results for the careful review of potential scholarly readers.

External threats to validity. External threats to the validity of the study occur when researchers “draw incorrect inferences from the sample data to other persons, other settings, and past or future situations” (Creswell, 2014, p. 176). The results of this study can only be generalized to populations and settings displaying the same characteristics as the study population and setting, within the time bounds of the study. Table 2, below, outlines four threats to the external validity of this research. It is as Wilkinson (1999) noted, “Sometimes the case for the representativeness of a convenience sample can be strengthened by explicit comparison of sample characteristics with those of a defined population across a wide range of variables.” (p. 595).

Table 1

Threats to internal validity

Internal Threat	Description	Possibilities within this study
Mortality	the situation of students dropping out from the study (e.g., dropping a class, withdrawing from the institution)	Underperformance contributes to student attrition (e.g., academic dismissal, loss of financial aid, etc.)

History	the occurrence of events or conditions that run peripherally to the study but may influence the outcome.	Contextual factors of student success unaccounted for in this study (e.g., hours worked, participation in extra-curricular activities, familial factors, and changes in academic program)
Maturation	the characteristic changes of participants due, at least in part, to the passage of time.	upperclassmen have refined their skills and strategies for learning
Researcher Bias	when the researcher has a predisposition towards a particular outcome	the collection, cleaning, and analysis of the data may have been predisposed to the sentiments of the researcher

Note. Summarized from Campbell and Stanley (2015)

Table 2

Threats to external validity

External Threat	Description	Possibilities within this study
Population Validity	the extent to which findings are generalizable from the studied sample to other populations	population characteristics were outlined in the descriptives table in Chapter 4 of this study
Ecological Validity	refers to the extent to which findings from a study can be generalized across settings, conditions, variables, and contexts.	the results may only be generalizable to institutions with similar characteristics
Temporal Validity	the extent to which research results can be generalized across time	considering the rate at which technology continues to enhance efficiencies in the classroom, the effects of recording attendance may not be generalizable in future iterations of the study
Researcher Bias	poses a threat to external validity because the findings may be dependent, in part, on the characteristics and values of the researcher;	to the extent future researchers' beliefs diverge from this researcher, so too may inferences drawn from similar data

Note. Summarized from Campbell and Stanley (2015)

Organization of this Study

This study was organized into five chapters, three of which are currently present. Those that are currently present include chapters one, two, and three. Chapter One was the introduction to the study. It included the background, statement of the problem, framework, purpose, significance of this study, definition of terms, delimitations, and limitations. Chapter Two provided a review of the literature relevant to this topic. The review presented four theses pertaining to (a) the relevance of attendance in student success, (b) the extent to which attendance impacts student success, (c) philosophical considerations regarding compulsory attendance policies, and (d) an overview of early-alert systems that may impact student behavior without overtly dictating it. Along with those four theses, historical narratives of accountability in higher education and early alerts were also included. Chapter three provided a clear and thorough description of the method used within this study. Sections of chapter three included, the research questions, research design, data collection procedures, as well as the proposed process of data analysis. Chapter four included a write-up of the results, following the procedures outlined in chapter three. Contained within chapter five was a discussion on the practical implications of the results detailed in chapter four as well as recommendations for future research.

CHAPTER II

REVIEW OF LITERATURE

The characterizations of institutional success have shifted dramatically over the past 75 years. Whereas once low retention and graduation rates were akin to institutional prestige, attesting to the rigor of the program, those same low rates now draw ire from the community, government, and even other institutions (Barefoot, 2004). The Department of Education's landmark edict of a "rising tide of mediocrity" within higher education perhaps served as the catalyst for today's 'Age of Accountability' in education. College administrators are forced to balance the inputs and outputs of the institution; developing ways to increase access to marginalized populations without decreasing retention and graduation rates (Yorke & Longden, 2004). The complexity of this challenge cannot be overstated, as diversity increases (racial, socioeconomic, geographic, mental wellness, etc.), so to do the needs of those populations, subsequently increasing the programming and personnel necessary to minister to those needs (Tinto, 2005; Yorke & Longden, 2004). This paradox is exacerbated by the challenge to maximize efficiency; increasing performance while decreasing the resources necessary to accomplish such improvement. With the prospect of performance-based funding from state and federal sources, many schools simply cannot afford to operate with high attrition rates (Barefoot, 2004). Consequently, student affairs and academic success professionals have sought ways to identify those students who are most likely to succeed at their institution. This has led to the advent of risk prediction in higher education.

The myriad factors which contribute to student success encompass a holistic view of student needs. Vincent Tinto's seminal work *Leaving College: Rethinking the Causes*

and Cures of Student Attrition described these factors in great detail, outlining the influences of finances, social connection, student affect, and cognitive ability on students' proclivity to retain and persist. Student and academic affairs practitioners often seek to *predict* these risks and the overall likelihood of student retention to intervene when necessary and proactively help students overcome these barriers. High school grade point average, standardized test scores, and placement exams are used to indicate a student's aptitude for academic coursework. Demographic indicators, like socioeconomic status, race/ethnicity, and first-generation status are often included among non-academic risk indicators. Furthermore, instruments like the ACT Engage, formerly known as the Student Readiness Inventory, are used to identify psychosocial risk factors – like *academic discipline* and *general determination* (Allen, Robbins, and Sawyer, 2010). These measures help provide a holistic depiction of the *likelihood* of student performance. However, this depiction is not a guarantee and many of these pre-college indicators neglect a fundamental component of student success, student behavior. Student involvement proves to be a predominant factor in student success (Astin, 1999). The ability to proactively identify and subsequently intervene when student behaviors become a detriment to their own success is a critical element for institutions to employ. Chief among these behaviors, is classroom attendance.

Although the relationship between attendance and student performance seems intuitive, the topic has been wrought with controversy over the past century. An even greater point of contention arises when the focus shifts to any notion of mandating attendance, with critics arguing it violates the academic freedom rights of both faculty and undergraduates (St. Clair, 1999). So not only do senior administrators have to

balance the input-output paradox of higher education while juggling the efficiency conundrum, they must also balance the values of academic freedom in the ‘Age of Accountability.’ A balance may exist however, with the use of early alert systems which are informed by behavior and are subsequently used to inform behavior. The question remains, however, if designing an early alert system that predicts academic performance based upon student attendance data is a viable endeavor for senior administrators, faculty, and student affairs professionals. To logically arrive at this conclusion, a specific sequence of questions must be answered.

First, it must be determined if student success is, indeed, important. If student success is important, how should success be defined? Once a definition is established, the two logical questions that follow are (a) what factors contribute to student success and (b) what gaps in both the theory and practice of student success still remain? Insofar that attendance is one behavioral manifestation of student engagement, it was argued in this paper that the impact of attendance on student success is, perhaps, the greatest enigma in student success theory (Astin, 1984; Donovan & Radosevich, 1999; Crede et al., 2010). Because of the potential salience of attendance on student success, understanding the degree of impact attendance has on student success is of the utmost importance. Upon establishing this relationship, it must be understood why absenteeism is still so prevalent. From this understanding comes the opportunity to identify the most prudent action to attempt to curb absenteeism. Are policies and mandates the most appropriate action? If not, what other opportunities exist? Following this logic and by answering these questions, one can provide long-awaited solutions to help increase student success.

Is the Success of Students Important?

Yorke and Longden (2004) asserted “the importance of student success in higher education is incontestable” (p. 5). They identified three primary stakeholders who inherently benefit from the success of students—students, the institution, and the state. This triad has been dubbed the “triangle of coordination” (Clark, 1983, p. 143). The interdependence of these three entities insulates the mutual interests for increasing student success and establishes mutual accountability to the other two entities; what Burke (2005) refers to as the “accountability triangle” (pp. 22-23).

When a student graduates, the student benefits from the access to better paying jobs and an increased quality of life (Abel & Deitz, 2014). The institution benefits from an increase in positive public perception, leading to more government funding and increased student interest. Government benefits from having a more well-educated and highly skilled workforce, subsequently decreasing societal dependence on government sponsored programs (i.e., unemployment checks, Medicaid, etc.) and allowing excess revenue to be devoted to other areas which increase the quality of life for its citizens.

From a financial standpoint, students are more inclined to view their education as an investment and will choose schools that represent the greatest potential for a high return on investment. Despite the stagnation in wage growth in the wake of the Great Recession, a college degree—whether associate’s or bachelor’s—still represents a worthwhile investment (Abel & Deitz, 2014). Because of the societal benefits, government entities are more inclined to devote resources to institutions which represent the greatest return on state investment. As constituents seek government intervention to resolve inequities in education, legislators redirect that pressure onto educational

institutions. It is as Tinto (2005) described, “policymakers have increased demands for publicly funded systems and institutions to strive for and document better performance on key outcome indicators” (p 10). This pressure often manifests as funding being tied to educational outcomes (Miao, 2012; Dougherty et al., 2016). Consequently, educational administrators enact policies to work towards those outcomes. The state of Washington for instance, in response to the Student Achievement Initiative-a performance-based funding measure which incentivized credential completion-experienced a surge of students completing certificate programs (Hillman, Tandberg, & Fryar, 2015). Although this was a largely unintended consequence, as the initiative sought to increase associate degree completion, it does demonstrate the institution’s responsiveness to government funding.

In an effort to maximize the impact of limited resources, the performance-based mentality is adopted by administrators and trickles down to academic departments, individual faculty, and their specific courses. Schools are most inclined to invest in students and programming which yields the greatest return on investment, so as to provide the most good to the greatest number of people. This investment manifests both in merit-based student aid, as well as co-curricular programming. Indiana University Southeastern, for example, piloted a Residential Learning Community to increase the retention and persistence of at-risk students. This was in direct response to an Indiana Commission on Higher Education funding measure which used student persistence as a performance metric. However, the Residential Learning Community did not receive funding renewal as it was not viewed as financially sustainable, despite showing a positive impact on student retention that would have likely resulted in increased student

persistence (Hall & O’Neal, 2016). These examples require acknowledgement that academic decisions and policies are driven, at the very least indirectly, by economic and legislative factors (Tin, 2014).

The ever-increasing consumer knowledge base of prospective students, families, and society results in the proliferation of demand for tangible metrics of success, most notably retention and graduation rates. These benefits and interests represent a supply-side mentality of enrollment, where greater enrollment and attainment begets greater funding. Internal and external benchmarking become necessary to provide a basis for evaluating and enhancing services. However, these benchmarks are predicated on graduation, which is fundamentally reliant upon retention. Retention as it is currently defined is rather limited and, if used as the primary determinant of institutional success, could render counterproductive. For example, if institutions were solely focused on retention, they would likely exclude those who pose greater attrition risk (Yorke & Longden, 2004). Currently, attrition risk tends to be greatest among marginalized populations-low SES, minorities, first-generation students-thus this limited view of admission would fundamentally reinforce socioeconomic inequalities. As such, colleges and universities have a vested interest in furthering social justice efforts by offering access and opportunity to higher risk populations. These myriad interests and benefits of student success, although quite clear, still require a more robust understanding of how *student success* ought to be defined.

What Constitutes Student Success?

In an attempt to create a framework for higher education professionals, including researchers and practitioners, Perna and Thomas (2006) identified 10 indicators for

student success, clustered into four domains: (a) College Readiness, (b) College Enrollment, (c) College Achievement, and (d) Post-college attainment. They went on to assert that the 10 indices are interwoven into a greater, longitudinal understanding of student success which is predicated on the contextual factors and idiosyncrasies of the population being examined. This context, even for individual institutions, has shifted over time.

In 17th and 18th century America, the notions of accessibility, enrollment, and even degree completion were of little importance to now prestigious schools (i.e., Yale, Princeton). Their primary focus was on preparing a select few, young men to become gentlemen and men of great consequence and influence (Thelin, 2011). It therefore appears the initial role of higher education was to provide students enough education to meet the needs of the immediate surrounding community; degree attainment was not a primary concern. This model lasted for the first two centuries of American higher education, from the founding of Harvard (1636) through the enactment of the Morrill Land Grant Act of 1862, which legislated the establishment of institutions in every state to meet the agricultural needs of the state. The idea of college readiness, accessibility, and degree attainment would not manifest until years later.

During the time of the Industrial Revolution, American society experienced an influx of college seeking students, with approximately 33% of high school graduates pursuing additional schooling (Jurgens, 2010). This increased supply of students gave rise to 'elitist' institutions, who could be selective in their admission processes. Young students from more marginalized populations (i.e., women, African Americans, Jewish and Catholic immigrants) were often the ones excluded. This selectivity lead to the

establishment of Women's colleges and religious universities to educate those otherwise excluded (Tinto, 2005). Although pre-dating the Industrial Revolution, the Second Morrill Act of 1890 led to the establishment of many land grant institutions for African American students as the Act forbade racially discriminatory admission policies (National Research Council, 1995). To date, many of these colleges remain highly regarded for their abilities to enroll students from historically marginalized populations and serve as examples of schools that advance social justice challenges in society.

For the next 50 years, both because of- and in spite of- two World Wars, colleges and universities experienced an even greater demand for higher education. This demand, however, came from a broader and more diverse group of students. First, the Great Depression increased the demand for junior college education, where students could learn requisite job skills for gainful employment (Jurgens, 2010). After World War II, the GI Bill afforded the opportunity of post-secondary education to a growing number of students from low socioeconomic backgrounds. Similarly, the Civil Rights movement provided greater access for racial minorities. As the student population diversified, so too did the mentality of students. Tinto (2005) noted, "students began to move away from learning as the primary goal of their education to making the grades that would help them in their future" (p. 19). This emerging emphasis on degree attainment necessitated an emphasis on providing better service to a more intellectually, socially, and racially diverse student body; *retention* and *persistence* to degree completion became fundamental metrics of student success.

These metrics have been largely institutionally focused metrics, where success is defined in the aggregate and, at times, neglects the contextual factors that are nuanced to

each student. The *Student Progress Unit* is a model employed in Australia that takes a more student-centered approach to education (Yorke & Longden, 2004). Success is measured and evaluated per class-or unit-instead of strictly degree completion. This helps account for those students in transition and part-time students who do not necessarily enroll to complete a credential. Thus, the Student Progress Unit provides an opportunity to define success as appropriate for the student needs (Yorke & Longden, 2004). Interestingly, this harkens back to the middle of the 19th century, where Tinto (2005) states “the time spent at college was idiosyncratic, depending more on the needs and wishes of the students’ families than on the requirements of the institution” (p. 16). Higher education in 21st century America seems to be reverting to a more student-centric model, perhaps in response to the proliferation of ‘non-traditional’ student enrollment. Choy (2002) found that as many as 73% of students could be considered ‘non-traditional’ and suggested the full-time, daytime structure may not fit their needs. As this trend continues, the flexibility and adaptability of colleges becomes all the more apparent and traditional measures of success (i.e., retention) may no longer be altogether appropriate (Yorke & Longden, 2004).

With an increased number of students attending multiple institutions along their path towards graduation, retention appears to be a less-than-adequate measure of institutional success (Adelman, 2006). Institutional transfer is among the 10 indices Perna and Thomas (2006) include in their conceptual framework. The two indices within the achievement domain that remain are *academic* performance (grades) and *persistence*. Because a more student-centric model of success may encourage a student to transfer, and thus not persist within the institution, persistence appears insufficient; rendering

academic grades the most germane index of institutional student success, at both aggregate and individual unit levels. Research suggests “using grades to represent levels of academic achievement is almost universal practice” (Sadler, 2009, p. 807). Although quantitative metrics, like grades, have a longstanding history of criticism (i.e., Crooks, 1933; Kohn, 2011), the ubiquity with which they have been used suggests it is still a reasonable metric for measuring academic performance.

What Impacts Student Success? Where are the Knowledge Gaps?

Student success is impacted by a wide range of factors, including but not limited to affective (Allen, Robbins, & Sawyer, 2010), behavioral (Robbins, Lauver, Le, Davis, & Langley, 2004), cognitive (Brown et al., 2008), and demographic characteristics (Engle, 2007; Howard, 2010; Reardon, 2013). Despite the efforts of student affairs professionals to mitigate these differences and close gaps in achievement, the national 6-year graduation rate remains relatively stagnant at 60% (National Center for Educational Statistics, 2018). This suggests other factors have yet to be fully considered.

Some of the most prominent achievement gaps have been noticed along demographic lines. Engle (2007) reviewed research on first-generation college students. She focused on a wide range of characteristics, including demographic, educational preparedness, and first-generation status. Engle (2007) also explored various intervention strategies intended to meet the needs of first-generation students. Interventions for first-generation status are designed to help students overcome inherent barriers, as opposed to changing the nature of the risk factor. As she noted, “increasing postsecondary opportunity for these students by changing the level of their parents’ education is not practical” (p. 27).

Along those same lines, Reardon (2013) studied the relationship between academic achievement (e.g., standardized mathematics and reading scores) and family income for students in the United States, with data spanning 50 years. His research revealed that although substantial progress had been made in terms of reducing the gaps in racial inequalities, less progress was noticed in terms of achievement along economic lines. He noted that both achievement gaps remain high, but economic inequality had surpassed racial inequality in education outcomes.

Howard (2010) provided a comprehensive perspective on the lived experiences of minority students. He noted that, despite the good intentions, some early theories—most notably the cultural deprivation paradigm—entrenched cultural stereotypes and resulted in teachers holding lower expectations of minority and low-income students, subsequently teaching to lower expectations. Later paradigms, like the cultural differences paradigm, “provided a significant antidote to the cultural deficit paradigm” (p. x) and framed cultural differences in a positive light. It was reiterated, however, that despite the positive reframing, practitioners needed to remain cognizant of unintentionally stereotyping their students as it could impact other non-cognitive factors of student success.

Robbins, Lauver, Le, Davis, and Langley (2004) examined both psychosocial factors and study skill factors and their relationship with college achievement (grades and retention) by meta-analyzing 109 studies. The psychosocial factors were organized into nine constructs, including motivation, self-efficacy, self-concept, and academic skills. Each of the factors were positively related to academic performance. They found the best predictors for GPA were academic self-efficacy ($\rho = .496$) and achievement motivation (ρ

= .303). The study did not account for institutional selectivity nor the size of the institution, which they directed further research to consider.

Allen, Robbins, and Sawyer (2010), furthered the work of Robbins et al. (2004) and summarized evidence pertaining to the validity of psychosocial factors as predictors of academic performance, to guide student affairs professionals in their intervention strategies. The authors noted however, “improvements in identification are only of value if the subsequent interventions have a positive effect on student outcomes” (p. 11). Brown et al. (2008) suggested a potentially valuable framework for designing such interventions. They used both meta-analytic and structural equation methodologies to study Social Cognitive Career Theory’s (SCCT) academic performance model. Their results demonstrated that both cognitive ability and high school GPA related to college performance, as they had expected, but by different means than they had anticipated. Prior performance (i.e., HS GPA) was more strongly related to self-efficacy, whereas general cognitive ability (i.e., ACT and SAT) had a stronger direct effect on college performance. Due to the limited attention *outcome expectations* received in academic performance literature, they were unable to include outcome expectations as variables in the path analyses. Outcome expectations were defined as “beliefs about the consequences of engaging in academic tasks” (p. 299). They expected that outcome expectations would have a strong, unique link to academic performance and recommended more research be intentionally devoted to this particular variable. Despite the limitations regarding outcome expectations, they posited that the SSCT model may provide a reasonable framework for understanding the mechanisms by which students

achieve in college. As such, the SSCT model could prove to be a valuable framework for designing intervention strategies for at-risk students.

Although considerable efforts continue to be made with the intent of reducing achievement gaps along demographic characteristics, the aggregate 6-year graduation rates have remained relatively stagnant. This suggests that interventions for other characteristics (e.g., psychosocial or behavioral) may still be necessary. Several examples have demonstrated the interdependence of demographic factors and psychosocial factors. Whereas research abounds with intervention strategies for influencing student affect, recommended interventions for student academic behavior remain understated. Chief among these academic behaviors, is that of student classroom attendance.

Instructional Delivery Modalities

For educators to measure academic performance, and subsequently improve upon their efforts, they must understand the environments in which learning takes place. With the advent of the ‘technological revolution,’ colleges and universities are finding not only new revenue streams, but new opportunities for reaching a broader audience and new strategies for teaching. Electronic learning, or e-learning, is on the rise. Seaman, Allen, and Seaman (2018) noted that in 2016, more than 6.5 million students (31%) enrolled in at least one online course. Teachers are leveraging technology to make courses more collaborative, even blending the use of face-to-face sessions as well as online sessions. Similarly, instructors are ‘flipping the classroom’ by assigning more of the didactic learning for homework and applying those principles during in-class projects (Islam, Salam, Bhuiyan, & Daud, 2018). Even virtual reality is being considered for class

instruction (Küçük, Kapakin, & Göktaş, 2016). Despite the proliferation of technological alternatives to seated instruction, there is still a great amount of debate and criticism surrounding the use of these innovations.

E-learning. Zhang, Zhao, Zhou, and Nunamaker (2004) defined e-learning as “technology-based learning in which learning materials are delivered electronically to remote learners via a computer network” (p. 76). In their research, Zhang et al. (2004) argued that e-learning was a more student-centered format for instruction, as it yielded control to the students. Face-to-face courses, in their depiction, are predicated on instructors controlling the lecture content and the speed in which that content is delivered. They tested this notion in replicated experiments, with a control group (in-class lecture) and the experimental group (e-learning). What they found is that students in the e-learning groups earned mean test grades nearly 10% higher ($M_{\text{face-to-face}} = 9.24$; $M_{\text{e-learning}} = 10.88$). They attempted to explain this in terms of meeting students’ needs. In their estimation, students in a seated classroom rarely ask questions and often neglect to ask for a topic or statement to be reviewed during the lecture. In an e-learning environment however, students can stop a lecture at any point, and re-watch or re-listen to a portion as needed, until the information is adequately learned. Similarly, a student can slow the pace down, to glean as much information as possible, without fear of hindering the learning experiences of others in the class. They claimed that yielding control of the content and pacing of class afforded students the best opportunity to learn.

However, Bains, Reynolds, McDonald, and Sherriff (2011) compared e-learning, blended learning, and face-to-face learning across student outcomes and satisfaction among students in a Dental program. Using a prospective cluster, randomized trial to

compare four groups, Bains et al. (2011) found the differences between the performance of face-to-face learning groups and blended learning groups were not statistically significant. E-learning groups however, scored statistically significantly lower ($p < .05$) on post-test questions than the other groups. Interestingly, students rated face-to-face learning as the least favorable modality for instruction, with blended being most favorable.

Bell and Federman (2013) noted the recent growth of e-learning in higher education and attributed this rise to administrators seeking new revenue streams and increased access to higher education, as well as providing greater flexibility in student scheduling. They reviewed several meta-analyses to determine the extent to which e-learning differs in its effectiveness in teaching, when compared with other modalities. They found that e-learning was equally as effective as the other modalities when instructional conditions were held constant. Their review also illuminated several inherent barriers to access, as those in rural areas and lower income students may struggle accessing internet and may not have access to sufficient technology for accessing the e-learning classrooms. So, although e-learning could be as effective as in-class instruction, it still proves to be a barrier to populations already marginalized by the educational system.

Lecture Capture. Video recordings of lecture allow students to review sections of lecture that were unclear. Williams, Aguilar-Roca, and O'Dowd (2016) mentioned that video recordings were popular among students but also noted the concern that recorded lectures may reduce in-class attendance. In their study of an undergraduate introductory biology class with daily video podcasts, they found that attendance rates

were relatively high (89.5%) despite a majority of students utilizing podcasts. However, this usage did not demonstrate a large effect on exam performance, representing less than 3% of the variance on exam scores.

Varao-Sousa and Kingstone (2015) investigated the extent to which classroom presentation style impacted memory, mind wandering, and the subjective factors of interest and motivation. They examined this difference among live lectures compared to video lectures and the learning experiences of those students. Students were asked to report mind wandering during lecture and subsequently completed a memory test. To account for any confounding variables associated with student aptitudes, each student attended one live lecture and one recorded lecture. Their results suggested that lecture format affected students' memory performance but did not impact mind wandering. Students who attended the live lectures performed better on the memory recall assessment. Students also reported increased motivation in the live lectures.

Beyond video recordings, technology continues to enhance the learning experiences of students. One such example is Küçük, Kapakin, and Göktaş (2016) who studied the effects of Mobile Augmented Reality (mAR) on students' academic achievement and cognitive load. In their study, students utilized a MagicBook which "integrat[ed] virtual learning objects into the real world and allow[ed] users to interact with the environment using mobile devices" (p. 411). They utilized a random sample of 70 second-year undergraduate students with 34 students in the experimental group. Students in the experimental group, those who used the MagicBook, recorded higher achievement and lower cognitive load. They argued that the augmented reality tool

allowed students to synthesize content on their own time, at their own pace, and thus contributed to the increased learning outcomes.

Computer based learning. Along with mobile Augmented Reality and e-learning, computer-based learning has been shown to be effective, especially for developmental students. Developed in 1999 by Virginia Polytechnic Institute and State University (Virginia Tech), the Emporium Model is a pedagogical approach that eliminates lecture and instead utilizes “computer software combined with personalized, on-demand assistance” (Twigg, 2011, p. 26). The premise and assumption is that students learn mathematics by doing mathematics, not by listening to someone lecture about mathematics. This approach has been replicated at several institutions and has yielded improved pass rates ranging from 7% to 38% (Twigg, 2011). The implementation, however, appears to operate much like a traditional face-to-face course, where attendance is required at some institutions. Although the professor is not the primary teacher-the computer software is-the professor remains present to address questions from students as they may arise. The success of this model in developmental and gateway mathematics courses has prompted others to replicate the model for other types of courses.

Rais-Rohani and Walters (2014) studied the effectiveness of a redesigned engineering course (statics) using the emporium model. Students were assigned content to learn outside of class, including readings and instructional videos. Then, during class, students would use computer software to apply the principles they learned from their out-of-class work. From an administrative perspective, the instructional costs of the emporium model greatly decreased while not reducing the success rates for the statistics

course. In fact, after the pilot semester, the model was scaled for all the sections of Statics. The results indicated that students performed equally well in the Emporium model as they did in the traditional model. Bishop, Martirosyan, Saxon, and Lane (2017) found evidence that indirect instruction was more effective than direct instruction (i.e., instructor-centered learning). In a comparison of student-centered learning, computer-centered learning, and instructor-centered learning, they found students passed computer-centered learning courses at a rate of 63.2% ($n = 900$) which was statistically significantly greater than the pass rates for teacher-centered courses (58.2%, $n = 726$). The pass rate was highest, however, in student-centered learning courses (67.0%, $n = 900$). One prominent example of the student-centered approach is the ‘flipped classroom’ whereby students study outside of class and complete group work within the class period.

Flipped classrooms. Islam, Salam, Bhuiyan, and Daud (2018) studied 50 first-year dental students divided equally into two groups. The Dental Ergonomics topic was taught to the control group using the traditional model and the flipped classroom model to the experimental group. Upon the conclusion of each session, a mini test was conducted. They found that the group of students instructed with the flipped classroom method achieved slightly higher ($M = 91.67\%$) than the lectured group ($M = 89.58\%$). This difference was not statistically significant ($p = .28$). Although students conveyed positive feedback on the flipped classroom model, it is important to note that “they suggest all topics are not suitable [for the flipped model] which is similar to the opinion of the teachers” (p. 314). Once again, students and teachers alike, seemingly view face-to-face lectures as often superior.

Taglieri et al. (2017) sought to determine which instructional method, Team Based Learning (TBL) or traditional lecture-based learning, was superior in developing students' confidence and knowledge retention one year after instruction. They studied 147 students of the 283 enrolled (51.9%) in a lecture format and 222 of 305 (72.8%) enrolled in the Team Based Learning group using the knowledge assessment and survey. The mean assessment scores on content knowledge was higher for students in traditional lecture group ($M = 62.9$) than the TBL group ($M = 54.9$). This difference was statistically significant ($p = .001$). Interestingly, they noted that despite TBL increasing student engagement levels, knowledge retention after one year was lower than traditional lectures. The authors speculated that this difference was due to a change in the sequence of topic delivery, as faculty availability necessitated such a change. Although statistically significant, the effect on final course grade was 1.1%, which they suggested may not be educationally significant.

Despite these innovative methods and the promise they have shown, these studies and others (i.e., Johnson, Aragon, Shaik, & Palma-Rivas, 1999; Jones, 1999) seem to indicate that the traditional lecture style course is still the most effective method of instruction. Although e-learning is still in its relative infancy, current results have not demonstrated statistically significant enhancements over the traditional style. Methods like the Emporium model and the flipped classroom both have shown promise, and at times, superiority, but neither appear to be universally applicable. Furthermore, both still require in-class participation, which continues to substantiate the notion that in-class attendance is critical for student success.

A Brief History of Recording Attendance

The concept of a student record is a rather new phenomenon in education, especially post-secondary education, with origins dating back to the mid-1800s (Hutt, 2016). Despite its relative infancy, the student record has become inextricably woven into the very fabric of what defines enrollment. Students expect to have tangible evidence of the work they have completed, whether for school transfer or career attainment. Institutions similarly expect proof of student achievement. Lastly, government entities require accurate counts of student enrollment. All these needs manifest in a student record, the student transcript.

As the establishment of schools expanded in the early-1800s, so too did the need for accountability. Massachusetts, for example, tied community funding to student enrollment (Hutt, 2016). These methods for record keeping were wildly inconsistent, and at times inaccurately reported to secure more funding. Horace Mann, Massachusetts Secretary of Education at the time, called for a *common school* system that binned schools geographically into various school districts. Furthermore, the *report card* became a mechanism by which schools communicated with families the extent of progress each student made during the preceding year. These were relatively meaningless for post-secondary enrollment, as admission was predicated on testing, not credentials (Hutt, 2016).

In 1869, the concept of credentials became both important and necessary. Prior to then, every student in a college took the same courses. But upon the introduction of elective courses at Harvard University, it became incumbent upon institutions to record which courses each student enrolled in. Degrees were awarded upon a student's

completion of a specific number of courses, each requiring a set number of *contact hours*. A *credit-hour* has been defined as “the instructional unit for expressing quantitatively the time required for satisfactory mastery of a course of one class hour per week per term (semester or quarter)” (Heffernan, 1973, pp 65-66). From its inception, the idea of a credit-hour explicitly linked academic achievement to time in class interaction. For example, the University of Michigan Academic Catalog stated the requirements for degree completion and clarified the definition of a full-class, “24 or 26 full courses are required for the bachelor’s degree (full course equals 5 courses per week per semester, whether in lab, recitation or lecture)” (Heffernan, 1973, p. 62). This instructional unit has become a mainstay of higher education and is used in both administrative and legislative contexts. Faculty load, for instance, is predicated on the credit-unit and the amount of time inherent in teaching students for one hour per week per term. Similarly, government funding is tied not to the number of students enrolled, but the Full-Time Equivalent of students enrolled – a unit which is calculated using the credit-hour. In short, the credit-hour concept is integral to the very foundation of classification of student and faculty work, and inextricably tied to core administrative and legislative functions. With such dependence upon the credit-unit, a quantitative metric derived from the amount of time required in-class to master a certain amount of content, it only follows that in-class attendance must be a requisite for student success.

The second fundamental shift in the brief history of student attendance came during the Civil Rights Movement and was in response to President Johnson’s War on Poverty. The Higher Education Act of 1965 (HEA 1965), more precisely Title IV of the Act, “embodied the first explicit federal commitment to equalizing college opportunities

for needy students” (Gladieux, 1995, p. 44). That federal commitment came in the form of programming for underserved populations (e.g., Upward Bound), but most notably represented a substantial investment into funding for education. Programs like Federal Work Study and Guaranteed Student Loan helped to mitigate many financial barriers that had precluded underserved populations from accessing post-secondary education. With these funds, came accountability measures to ensure federal monies were being spent on students who genuinely maintained enrollment at the institution.

Pursuant to Title IV of the HEA 1965, when a student withdraws their enrollment from an institution, the school is required to determine the amount of federal aid that had been earned. This calculation, in the case of credit-bearing courses, is predicated on the student’s *Last Date of Attendance*. Up through the 60% point of the term, the institution is responsible for refunding any ‘unearned’ aid. When a student attends class at or beyond the 60% mark of the course, all student federal aid is deemed earned. (Higher Education Act of 1965, 2018). Because compliance with this act is required for eligibility to receive the corresponding funding, it is to be assumed that every school receiving this funding is monitoring student attendance to some degree.

It is worth noting, the threshold for earning aid is predicated on class attendance, not on work submission. Irrespective of how much work a student completes, or the marks a student earns via course assignments, the act of attending class serves as the basis for a student’s enrollment. This policy suggests that even the federal government acknowledges the necessity of class attendance. Interestingly, in her case against compulsory attendance policies, St. Clair (1999) cited a couple of necessary exceptions to her repudiation of mandated attendance policies. Among these examples, St. Clair

(1999) stated, “This does not imply that it is always inappropriate to institute an attendance policy. Some funding sources require monitoring attendance of students receiving financial aid, with some punishment for absenteeism.” (p. 179).

Between the proliferation of the credit-unit as the standard educational unit in higher education, and the noticeable ways in which federal funding is tied to attendance, the systematic embrace of attendance is inescapable. The standard unit for a course is predicated on presence in class, more so the submission of work completed. Similarly, federal funding metrics are also tied to the last date of attendance, not the last date of work submitted. It is reasonable to conclude from these two examples, that executive leadership, both for institutions, individually, and the federal government, at-large, believe class attendance is meaningful for student success.

Is Attendance Meaningful for Student Success?

Researchers have been studying the relationship between class attendance and academic performance for nearly a century (Turner, 1927). Intuitively, students, faculty, and administrators understand the impetus for attending class. Interestingly however, many early studies which tested this assumption have presented conflicting data, bringing the actual relationship between these two phenomena into question and leading others to claim attendance may be a proxy for student achievement (Chung, 2004; Durden & Ellis, 2003). More recent literature, especially that which has been published within the past 20 years, appears to more consistently support the notion that higher attendance does, in fact, relate to higher academic performance. These studies typically utilize one of two dependent variables to define academic performance, either *exam performance* or *final grades*. These formative (exams) and summative (final grades) approaches to measuring

the extent to which attendance relates to academic performance have brought meaningful results for practitioners and researchers, alike.

Exam performance. Those who have chosen to rely on exam performance (i.e., Lin, 2014; Marburger, 2001; Stanca, 2008) argue exam performance offers a better indicator of the relationship between these two variables, attendance and performance, as content is derived specifically from classroom activities, discussions, and lecture notes. Summative measures (i.e., final grades) are often comprised of confounding factors like presentations, essays, and other projects that are often completed outside of the classroom. Furthermore, faculty who include participation points as a component of their final grades, inherently influence the relationship by rewarding students simply for showing up to class. They view this as problematic as the ultimate question at hand is on the import of attendance as a potential predictor of learning, which subsequently manifests in students' academic performance. The formative measure of exam performance, they attest, offers a more robust metric by which researchers can firmly conclude the extent to which a relationship may exist. Logically, if attendance impacts students' exam grades and exam grades influence final grades, then attendance would inevitably impact final grades.

Recently, Lukkarinena, Koivukangasa, and Seppälä (2016) studied the relationship between attendance and exam performance. In their study, students were placed into two primary populations, (a) those who attended class and took the final exam and (b) those who missed class but studied independently prior to taking the exam. Despite compelling reasons for the absenteeism of the latter group, and their own study efforts, Lukkarinena et al. (2016) demonstrated the statistically significant, positive

impact of attendance on exam performance. The generalizability of many of these studies are rather limited, however, as they often examine populations with small sample sizes (e.g., [$n = 29$] Lukkarinen et al., 2016) or the study was delimited to a specific subject (i.e., Chung, 2004; Moore, 2006). To rectify these types of limitations, specifically those of Colby (2004), Newman-Ford, Fitzgibbons, Lloyd, and Thomas (2008) conducted a similar study using attendance data spanning 22 course modules and four subjects. They affirmed the *70% Rule* offered by Colby (2004) by presenting their findings that students who miss 30% of class, thus failing to attend at least 70% of class, have a 1 in 3 chance of failing the course and a 6 in 7 chance of performing at or below average on their assessment. Furthermore, Newman-Ford et al. (2008) cite the *80% Rule* (Colby, 2004), as the “trigger point for action” (p. 714), noting that those who miss 20% of class, thus failing to attend at least 80% of class, have the same rate of failure (33.3%) on their final exam as those who miss 30% of class. These results on the impact of amassed absences on final exam performance certainly affirm the argument for correlation but fail to demonstrate or even suggest causality.

At a micro-level, Marburger (2001) maintained scrupulous notes on student attendance and the lesson plan for each class period, as well as the specific exam questions derived from each specific class session. What was discovered is that students who missed a specific class period were statistically significantly more prone to answer the corresponding exam question incorrectly. This is important as it does suggest that, although students may acquire lecture notes from a peer, those study skills are not necessarily enough to gather the requisite information that appears on exams. Because of the sequential nature of learning assessments, where the content is taught prior to the

exam, these results suggest attending class may improve a student's likelihood of performing better on the exam. Although the mere fact of a relationship is important, the degree of impact attendance has on exam performance establishes the necessity for attending class.

Researchers have differed substantially on the amount of influence attendance has on exam performance, although each study has demonstrated a positive impact. As early as 2001, Shimoff and Catania (2001) found an increase in the percentage of correct exam scores from 77.1% to 81.5%, simply by recording attendance. Marburger (2001) presented evidence that the impact was relatively similar, where attendance increased exam performance by 2%-4%. Absent from the literature, however, was any calculation of the "average treatment effect on the treated" (Chen & Lin, 2008, p. 213). Chen and Lin (2008) contested that most of the literature relied on the average treatment effect, using weighted averages for those who attended and those who missed class. Although important, they assert that the average treatment effect actually underestimates the effect for those who attend class. Accordingly, they sought to create a randomized experimental design to analyze differences in the calculated effects for the two populations. They found an *average effect on the treated* ranged from 9% to as high as 18%, whereas the same data showed only a 5% increase in performance when the researchers used analyses similar to previous research (average treatment effect).

Chen and Lin (2008) contend that many studies neglect to consider the compounding impact of attendance on exam performance. Arguably, if teachers are scaffolding their lessons, then an absence early in the semester may impact performance on the adjacent exam as well as any subsequent exam that is predicated on information

otherwise gleaned early in the semester. Thus, the *cumulative effects model* (Lin & Chen, 2006) may better explain the lasting, or cumulative, impact of attendance on performance. Lin and Chen (2006) not only noted a 4% improvement on exam performance for attending lectures, but they also found a marginal impact of close to 4% for cumulative attendance. Interestingly, their students showed a reduction of nearly 0.4% on the impact of *attendance* when *cumulative attendance* was accounted for, substantiating their argument for the cumulative attendance effect. Understanding the influence of attendance, formative (i.e., mid-semester performance) and summative (i.e., final exam performance) measures of academic performance and those scores' impact on the final course grade, it is logical to deduce that attendance would similarly affect course outcomes.

Grade performance. Whereas contemporary research has ostensibly demonstrated the salience of attendance for influencing learning, as measured by exam performance, the relationship between attendance and course grade is arguably more important. Insofar that students receive course credit based upon final course grade; although implicitly related, high exam performance does not necessarily ensure a high final grade, nor does low performance beget a low final grade. The extent to which course grades are determined by presentation, group project, and essay scores, may diminish the relationship between exam scores and final grades. Certainly, the quantity and type of graded assignments may confound the relationship between attendance and final grade to a greater extent than the on-exam performance. That is precisely the reason though, it is critical to understand the relationship between attendance and course grade. Shimoff and Catania (2001) point out, this relationship may be direct, indirect, or perhaps

both. Directly, some instructors may award *participation points* or otherwise grant credit simply for showing up to class. Indirectly, and as noted in the previous section, the instructor may draw exam questions from content covered solely in class, thereby favoring students who attend specific lessons. The consequence of these competing, or perhaps complementary, influences is that researchers must account and control for a greater number of confounding variables, including affective (e.g., anxiety, control), behavioral (e.g., motivation, distributed practice), cognitive (e.g., prior GPA), and demographic variable (e.g., gender, race, first-generation status, etc.). It is for many of these reasons, why Durden and Ellis (2003) claim attendance is better thought of as a proxy for achievement; where attendance is the manifestation of other behavioral factors in student performance.

Affective. Students who are chronically absent “may be masking some more deeply-seated reasons for not attending lectures” (Moore et al., 2008, p. 21). Students under high levels of performance anxiety may engage in avoidance behaviors, exacerbating the consequences of an instance of poor performance. When a student experiences considerable stress, they may suffer from an inability to engage with lecture material, which could result in poor grade performance. The effects of anxiety can be mitigated by increasing students’ feelings of control (Morales, 2010).

Control represents the intersection of two components associated with Attribution Theory (Weiner, 2010), controllability and locus. Upon any given outcome, either positive or negative, a student has the opportunity to (a) reflect upon their culpability (locus) in that outcomes and (b) acknowledge any alternative choices which could have positively changed the outcome (controllability) (Collie, Martin, Malmberg, Hall, &

Ginns, 2015). In the context of attendance, if a student misses several lectures prior to an exam in which they performed poorly, a student who displays a high level of control would attribute their poor performance to their decision to skip class (internal locus; controllable). By choosing to attend class, the student could expect to improve their exam performance, thus influencing their behavior. Conversely, the poor test performance coincided with a verbal reprimand for excessive absences from the instructor, that same student may attribute their performance to a perception that the instructor does not like the student (external locus; uncontrollable). It is therefore suggested by some, that policies which seek to compel student attendance may inadvertently undermine students' feelings of control over their educational choices (St. Clair, 1999). This perceived lack of control can lead to feelings of anxiety and ultimately lead to behaviors which inhibit students' academic success.

Behavior. The effects of academic stress and anxiety can be offset by academically resilient behavior. Academic resilience was found to be negatively related to stress ($r = -0.55, p = <.001$; Leary & DeRosier, 2012) and anxiety ($r = -0.35, p = <.001$; Turner, Scott-Young, & Holdsworth, 2016). As academic resilience increases, student anxiety decreases. By developing resilient behavior, students can overcome the negative impact of stress and anxiety on academic performance. Martin and Marsh (2006) suggested that resilient students may actually benefit from a reasonable amount of anxiety as it creates a 'fight' response, as opposed to the 'flight' response presented earlier. As a result, students with this 'fight' response may demonstrate higher levels of motivation. Some researchers believe this motivation manifests in attending behavior.

Moore (2003) posits students who attend class are more motivated. This was affirmed by Durden and Ellis (2003) who found that motivation and attendance were related and recommend that any influence of attendance on performance must also account for motivation, lest the relationship between attendance and performance be overstated. Those who are more motivated are likely to exert greater effort into class, which manifests in tangible, behavioral ways that pay dividends throughout the semester. Contemporary literature is replete with evidence affirming the strong, positive relationship between motivation and student performance (Cotterill, 2015; Guy, Cornick, & Beckford, 2015; Lonn, Aguilar, & Teasley, 2014).

Because they are more motivated, these students are more apt to engage in learning behaviors like studying outside of class, seeking resources for assistance, and completing their homework on time; all of which are factors that impact final course grade. By studying more frequently, students are engaged in *distributed practice* (Donovan & Radosevich, 1999) as well as practices of over-learning, both of which have been correlated with higher grade performance (Crede et al., 2010). It is precisely these learning activities which happen outside of the classroom (i.e., studying, office hours, electronic engagement with course material, etc.) that Chung (2004) claims weakens the view of in-class teaching as the sole, or preferential modality for learning. Much of this learning may be further dependent upon student ability.

Cognitive. Crede et al. (2010) cite the predictive ability of prior academic achievement (e.g., high school grade point average and standardized test scores) in college attainment as evidence of how students' cognitive ability "influences the degree to which [they] are able to process, integrate, and remember material" (p. 273).

Onwuegbuzie, Bailey, and Daley (2000) found that both prior academic achievement ($r = .37, p < .001$) and expectations of achievement ($r = .35, p < .001$), both listed as cognitive variables, were positively related to foreign-language achievement; those relationships were both statistically significant.

In their study, Onwuegbuzie, Bailey, and Daley (2000) used regression analysis to compare the proportion of variance among cognitive and non-cognitive variables (e.g., affective, demographic, and personality) in predicting student achievement in foreign language courses. Although they found each of these variable types to be important, cognitive aptitude—classified as prior academic achievement—was found to have the greatest effect, followed by affective correlates (e.g., foreign-language anxiety). These results were consistent with the foundational research of their study, supporting the notion that cognitive ability has a greater impact than other factors of academic success. Their research underscored the interplay between cognitive ability and affective factors like anxiety and perceived scholastic competence. The interplay of various student success factors appears to be an important partnership in students' achievement.

Busato, Prins, Elshout, and Hamaker (2000) found that intellectual ability remained highly predictive of academic success, especially when coupled with motivation. This predictive ability is largely independent of studious behaviors however (Crede & Kuncel, 2008). In a meta-analysis whose results were inconsistent with previous literature, Crede and Kuncel (2008) found that behavioral factors, like study skills, were largely independent of previous achievement—classified by high school grade point average and standardized test scores. This is noteworthy, especially considering the strong relationship between study skills and academic performance, as

well as prior achievement and academic performance. As the effect of cognitive factors on student performance is enhanced by other factor types, the absence of behavioral factors, like study skills, from Busato et al. (2000) and Onwuegbuzie et al. (2008) is important. This not only presents an opportunity, but also necessitates future research to further understand the impact of student behaviors (e.g., attendance) on student success.

Demographic. Student success literature is replete with evidence demonstrating the independent relationship between socio-demographic factors and attainment. These achievement gaps are evident across gender (Sax, 2008) first-generation status (Engle, 2007), socioeconomic status (Reardon, 2013), and race (Howard, 2010). Furthermore, the effects of these characteristics can manifest in academic attitudes and behaviors that inhibit academic performance. Morales (2010) for instance, noted the impact low self-efficacy had on the academic resilience of African American males. Similarly, Macdonald (2016) found that *cultural congruence*-maintaining the integrity of one's culture-had an even stronger relationship with academic attainment for first-generation students than continuing generation students. As such, the expression of these various attitudes and behaviors may be a more genuine cause of poor performance, irrespective of students' attendance records.

These are but a few prominent examples of characteristics that contribute to the vexing student success conundrum; examples that potentially complicate any relationship between attendance and student performance. Thus, ample research must consider some, if not all, of these factors in conjunction with attendance to ascertain a more precise understanding of the extent to which attendance relates to course grades.

As it relates to cognitive ability, Dollinger, Mayja, and Huber (2008) found that although absenteeism was related to class performance, the extent of this difference was dependent upon student's level of prior academic achievement. They posited that higher achieving students would be more capable of independent learning (i.e., studying outside of class), which would mitigate the impact of class absences. However, their regression model for attendance displayed the steepest slope for students one standard deviation above the mean verbal ability score, thus attendance had a stronger impact for students who possessed greater academic ability. Interestingly, this notion that attendance benefits high achieving students more so than lower achieving students was affirmed by Snyder, Lee-Partridge, Jarmoszko, Petkova, & D'Onofrio (2014).

Using a quasi-experimental design, Snyder et al. (2014) surveyed 212 students across sections of communication and information science courses. They found that although a compulsory attendance policy was enough to reduce absenteeism, the differences between compulsory and non-compulsory attendance policies were not statistically significant. The only comparison with statistically significant differences was for students who had a grade point average over 3.2. They surmised from these results that cumulative grade point average is a confounding variable in testing the relationship between attendance and class performance. This concept seems to run contrary to presumptions that academic behavior of lower achieving students has a bi-directional relationship with academic performance.

Crede et al. (2010) synthesized the literature on the relationship between attendance, cognitive ability, affective measures, behaviors, and class performance. Their meta-analysis portrayed 69 studies from over 90 years and sampled more than

21,000 students; it represents the most comprehensive explanation of these relationships. Their research found that class attendance is a “better predictor of college grades than any other known predictor of academic performance” (p. 272). This bold assertion places attendance as the premier predictor of success, outperforming cognitive abilities (e.g., prior performance, standardized test scores) as well as study behaviors, and shows virtually no influence from student characteristics like motivation. These findings presumably dismiss Durden and Ellis (2003), insofar that attendance does not appear to be a proxy for achievement, but in fact demonstrates a unique effect on course grade ($r = .44$, Crede et al., 2010). At the same time however, it would be inaccurate to conclude that attendance is the sole determinant of success and will unilaterally close the gaps in student achievement. With contemporary literature overwhelmingly supporting the salience of attending class, affirming the intuitions of students and faculty alike, it calls into question why chronic absenteeism persists. A thorough understanding of the motivations for class attendance, and perhaps the attitudes precipitating absenteeism, are entirely necessary to alter student behavior especially for a behavior that is the greatest known predictor of course success.

If Attendance is Meaningful to Student Success, Why is Absenteeism so Prevalent?

The answer to this question is largely rooted in social psychology and the complex interaction between attitudes and behaviors. Just prior to the start of a class session, students are faced with a choice, they can either (a) choose to attend class or (b) choose to not attend class. This decision is, generally, both conscious and voluntary. Except for critical life events, like a car accident, hospitalization, or temporary incarceration, students decide whether or not to attend class and subsequently act upon

that decision. This decision, more appropriately, students' behavior, is likely predicated on their attitudes towards attending that particular class. As Fazio (1990) stated

“An individual may analyze the costs and benefits of a particular behavior and, in so doing, deliberately reflect on the attitudes relevant to the behavioral decision.

These attitudes may serve as one of possibly many dimensions that are considered in arriving at a behavior plan, which may then be enacted” (p. 75).

The antecedents of these attitudes and subsequent strategies to influence attendance behavior need further examination.

Attitudes regarding attendance. Faculty attitudes diverge greatly on issues of attendance, including attitudes on whether students attend class as well as attitudes on whether or not faculty ought to be required to record attendance. Students' attitudes towards attendance, their rationales for attending or not-attending class are similarly divergent. These attitudes and the subsequent impact on behavior were explored below.

Faculty Attitudes. Classroom instructors are arguably, the first and best teachers of classroom expectations. Consequently, their attitudes on class attendance may have a tremendous influence on the attitudes held by students. It therefore comes as no surprise that the disparity in classroom attendance is rivaled only by the diversity of faculty attitudes on class attendance. A small sample of faculty can cover the entire spectrum where “some instructors don't care if students attend class at all ... [conversely] other instructors feel strongly about the importance of class attendance. Some instructors check attendance at every class; others don't check it at all” (Drugar, 2003, p. 350).

Underscoring the influence of faculty attitudes, Friedman, Rodriguez, and McComb

(2001) found students' perceptions that "the teacher doesn't notice or care that I am there" to be the second most prevalent reason for absent behavior.

For some faculty, their attitudes on attendance are self-serving. On one hand, the salience of attendance validates their role as educators. If students can perform well in the course without ever attending, the entire basis for their in-class lectures could be called into question. Some go so far as to "ensure [their] assumption is justified by basing some test questions on materials presented in class" (Shimoff & Catania, 2001, p. 192). Conversely, albeit just as self-serving, some faculty detest teaching so it is subsequently cogent that those faculty would express a more skeptical view of class attendance (Druger, 2003). Others maintain that students are adults and ought to be treated as such, whereby students can decide for themselves whether to attend class (Romer, 1993).

Moore and Jensen (2008) noted that most science instructors agree with the notion that attendance should be non-compulsory, but also attendance should not factor into student grades at all. They maintained the view that grades reflect subject-content mastery. On the opposite side of the spectrum, Druger (2003) argued that "*being there* is the essence of teaching and learning" (p. 351); that learning occurs within the unforeseen experiences that provide novel insight to a given topic. Because those experiences are unpredictable, but only happen within learning environments, the goal should be to increase the frequency of learning moments so as to increase the likelihood of those special moments. Druger (2003) agreed that attendance should not be mandated, but also acknowledged that when students simply show up for attendance sake alone, they occasionally experience one of those special moments and their view of the content, the lecture at large, or even their learning paradigm shifts precisely in that moment. How

these attitudes manifest, specifically within stated course attendance policies, may be at the discretion of the individual instructor but, at least theoretically, could be further influenced by educational entities of authority.

Despite the influential nature of faculty, the behaviors of students are not wholly determined by faculty attitudes. Even engaging faculty like Druger (2003) have students who choose to miss class and those faculty who bemoan the necessity of lectures will inevitably have students show up for their class sessions. Clearly, attitudes of students that guide their decision whether or not to attend draw influence from other factors too.

Student Attitudes. Although assumptions surrounding the import of class attendance may be self-serving among faculty, the same could be said for students. If class attendance is supposedly the preferred method for learning relevant course content, then we could expect to see near perfect attendance, save for situations of involuntary absenteeism (e.g., medical exigency). However, students' actions are ostensibly in direct contradiction to their attitudes and beliefs about in-class lectures. In a study on the explanations for attendance or absenteeism, it was found that more than 75% of students felt compelled to attend class and expressed feelings of guilt if they were to be absent (Friedman et al., 2001). This suggests students believe there to be something inherently unique and important about in-class learning. Of that same population, they found 70% of students chose to attend because they perceived content in class to be important, but their reasons for absenteeism pertained to factors unrelated to the importance of content.

Perhaps students' guilt stems from the traditional view of attendance that intuitively lingers with contemporary learners, "A generation ago, both in principle and in practice, attendance at class was not optional. Today, often in principle and almost

always in practice, it is” (Romer, 1993, p. 174). Although most students appear to believe attendance is important, their behavior affirms Romer (1993) that, in practice, attendance is still optional and that, although subjective and disparate, there remains a perceived threshold for an acceptable number of absences. When asked about the threshold for inconsequential absenteeism, 92% of students claimed their absences were within an acceptable amount (Marburger, 2001). This finding was irrespective of how often students actually missed. Remarkably, 100% of students who had less than six absences believed their behavior to be within reason and 73% of those with high absenteeism (more than six absences) also believed themselves to be within the threshold for acceptable absences. Perhaps those who missed, assuaged their concerns of missed content by gathering relevant information from classmates (Moore, 2006; Tiruneh, 2007) or studied via other learning platforms (Friedman et al., 2001). However, upon further examination, this notion elucidates another contradiction between attendance attitudes and behavior: that despite viewing seated-classes as superior, students often contradict this notion choosing to substitute asynchronous learning strategies in place of attendance.

As it relates specifically to in-class lectures, O’Malley and McCraw (1999) found that students preferred traditional lectures to online or hybrid formats, with students going so far as to state that synchronous online courses were inferior to face-to-face courses. Interestingly, habitual absenteeism appears to be promoted by students’ notion that they can adequately glean course content through other mechanisms; for example, accessing the lecture slides online or obtaining lecture notes from a classmate (Burd & Hodgson, 2005). Newman-Ford et al. (2008) noticed students’ preference for class notes instead of the textbook and posited this preference as a “strategic attempt by students to

identify the *most important* concepts covered in the text” (p. 700). Furthermore, Wentzel and Jacobs (2004) recorded considerably more absences when lecture notes are placed online. Despite students’ preference for traditional lecture, O’Malley and McCraw (1999) found students also wanted more online options, not because they were a superior modality for learning, but for the sake of expediency. In short, although they view learning as important and deem traditional face to face courses as a superior modality, students who miss class seem to value expediency even more, suggesting they have other competing interests and reasons for missing class.

Reasons for absenteeism. If students’ attitudes directed their behavior, it would be reasonable to deduce that the rising cost of higher education would lead to greater attendance, as students try to maximize their investment (Friedman et al., 2001). However, contemporary literature is rich with evidence demonstrating the preponderance of absenteeism, often justified by the expedience of other learning strategies. Research suggests students make a series of *trade-offs* throughout their educational journey (Burd & Hodgson, 2005). This paradigm is no more apparent than with the trade-offs made in missing class; where the time spent in class could potentially be better spent elsewhere. These opportunity costs could be driven by rational factors, like financial or health related decisions (Gump, 2004), but could also be recreationally motivated and determined by more trivial justifications like weather or having fun with friends (Friedman et al., 2001; Gump, 2004). As with prevailing attendance literature, many of these perceptions are predicated on intuition and anecdotal evidence. Many of the reasons offered by faculty and/or students are not empirically supported, adding to the consternation and complexity of absenteeism.

Financial and work considerations. With the rising cost of attending college, many students make the decision to work either part- or full-time. The rigidity of work schedules, the diminished energy from an increased workload, and the stress of multiple, major responsibilities could understandably undermine a student's proclivity to attend class. This assumption has been supported in literature (i.e., Longhurst, 1999). Conversely, speculation also exists that students who pay more for school, either receiving less parental support or as a product of out-of-state tuition, would have a greater stake in their success and subsequently be more engaged in classwork. Despite the fact that students surveyed in Friedman et al. (2001) cited *work obligations* as one of many reasons for not attending class, they did not find any statistically significant difference in attendance for students who were concurrently employed and enrolled, nor was there any evidence to suggest *educational funding* was statistically significantly related to attendance. So, although financial considerations may provide extemporaneous reasoning for an absence, it is not enough to explain chronic absenteeism.

Demographic and non-cognitive factors. Some in higher education maintain that attendance follows certain demographical tendencies. For instance, Gump (2004a) found sizeable differences between males and females, as well as upper- and under-classmen, in their reasoning for skipping class. He goes so far as to recommend faculty consider gender and class-standing in determining attendance policies for a given class. Conversely though, Friedman et al. (2001) found no statistically significant difference in attendance based upon gender or class standing. Where Gump (2004a) found *weather* to be a substantial consideration for upper-classmen but not under-classmen, one could reasonably attribute this to differences in campus residency-where upper-classmen are

more likely to commute. Once again however, Friedman et al. (2001) did not find a statistically significant difference in resident status. Similar to financial reasons, these demographic assumptions may explain spontaneous absences, it does not seem to be enough to explain chronic absenteeism. Some suspect these causes may be related to more affective correlates (Friedman et al., 2001; Gump, 2004b; Snyder et al., 2014).

Snyder et al. (2014) found evidence of *conscientiousness* relating to students' processing on the impact of missing a class but noted that although highly conscientious students may internalize the impact of absences, they may still miss more class than those with low conscientiousness. Interestingly, they note that even though students with lower conscientiousness may attend more, their engagement may be more physical than mental. *Motivation* has primarily been used to implicitly explain attendance, where students are motivated to attend class or those who attend more frequently possess more internal motivation (Gump, 2004b). Friedman et al. (2001) posited that because of *control*-a component of intrinsic motivation-students would be more apt to attend a class they freely chose, as opposed to one where students were required to take. Their hypothesis was correct. They found that students attended elective courses more often than required courses, in instances where neither had a stated attendance policy. Perhaps this understanding of internal motivation may manifest within the classroom too, whereby students may be more inclined to show up because policy 'forces' them to attend, but their attendance may not correspond to increased engagement. Interestingly, Shimoff and Catania (2001) found that simply requiring students to sign into class resulted in those students attending more frequently. This is in spite of both the control and experimental populations recording similar beliefs that recording attendance did not-or, in the case of

the control group, would not-impact their actual attendance. These factors, while compelling, are also less than satisfying in understanding the decision-making process for attending class or not. Beyond these non-cognitive factors, there may be other malleable factors to better compel student attendance.

Instructor and classroom environments. Student engagement-both attendance and participation-may be most influenced by the engagement of the classroom environment, most notably the instructor and the classroom structure. Druger (2003) underscored the impetus for an impassioned instructor and meaningful experiences to promote an engaging learning environment. Interestingly, instructor characteristics have been ranked high as both proponents and antagonists of students' rationale for attending class. When students attended class, one of the primary reasons they cited was *teacher influence* (i.e., the teacher is interesting; the teacher notices and cares when I am there) (Friedman et al., 2001, p. 129). Similarly, when stating reasons for skipping, *instructor-related* reasons (i.e., the teacher does not notice when I am there; the instructor is boring) (Friedman et al., 2001, pp. 130-131). This same study found that students were more likely to attend class taught by graduate teaching assistants, rather than actual professors. They hypothesized that when students are engaged in discussions, when their voices are heard and respected, and when the teacher notices them, they are more apt to attend and engage in class. This active learning is a valuable strategy for prompting attendance, whereas simple consumption of knowledge (i.e., strict lecture formats) dissuades attendance. These findings provide perhaps the greatest occasion for instructors to influence attendance. Furthermore, Friedman et al (2001) found this format to be more likely attributed to graduate teaching assistants' style, more so than professors. However, this

relationship may be mediated by specific attendance policies and the auspice of instructors actually taking attendance.

Policy and recording attendance. The debate over attendance policies provides yet another example of the disconnect between students' attitudes and their actual behaviors. In their study on the impact of recording attendance, Shimoff and Catania (2001) suspected that recording attendance would not impact student attendance. They divided a class of 114 students into two groups, the control and experimental group. The experimental group would be recording their attendance via a sign-in sheet, whereas the control group simply recorded attendance in the aggregate (counting how many students attended that class session). Despite assuring both populations that attendance would not factor into their final course grade, Shimoff and Catania (2001) ultimately concluded that those courses where students had to sign-in to class, resulted in higher student attendance than when the instructor simply counted the number of students in class each day. Friedman et al. (2001) also suggested that it was the attendance policies that mediated the relationship between instructor type and attendance. Snyder et al. (2014) supported this as well, for they found that "those students exposed to the compulsory attendance policy had fewer absences than those students who received the simple statement attendance policy. The threat of final grade reduction seems to accomplish its intent of encouraging students to come to class" (p. 437). Using a quasi-experimental design, they divided a class of 212 students into two groups. One group received a compulsory attendance policy that punished students for absences. The other group were given a policy that stated the expectation of attendance but would neither reward nor punish absenteeism. Once again, those subjected to the compulsory policy missed fewer classes, where M

represents the mean number of absences ($M = 0.86$, $SD = 1.23$, compared $M = 2.79$, $SD = 3.00$; $p < .01$). The tangible repercussions of absent behavior appear to be a compelling factor for students.

Students in Gump (2005) “claimed that the quizzes were helpful, that they forced them to keep on top of the material and prepared them for the midterm and final exams, which included objective questions similar to those appearing on the quizzes” (p. 24). However, when the dates of in-class quizzes were not clear, students expressed frustration as it impeded their sense of when missing class was inconsequential. This suggests students feel they only need to show up for class when there is something tangible to be gained (i.e., quiz points or points for attendance). A contentious debate exists over the use and efficacy of compulsory attendance policies, which may obfuscate the recommended actions of college administrators, faculty, and student success personnel.

If Attendance is Consequential, but Viewed as Optional, Why Not Mandate It?

As divergent as the attitudes on attendance are, so too are the arguments surrounding remedies for compelling class attendance. Compulsory attendance policies may seem like the logical answer but are wrought with myriad implications which may be counterproductive. These were described in the argument against compulsory attendance policies. Interestingly, a compromise may exist using an emerging concept which has shown promise in student success environments. These opportunities are described within this section.

For Compulsory Attendance Policies. Given the importance of attendance on student grades (i.e., Crede, Roch, & Kieszczynka, 2010), and the general desire of

educators to help their students learn, a cogent argument exists for mandating attendance. These compulsory policies manifest in a few different ways and often have the desired effect of increasing attendance. First, the overtly punitive means to compel attendance deduct points from the final course grade for excessive absences (Hancock, 1994; Snyder et al., 2014). Both studies demonstrated the efficacy of punitive measures in reducing absenteeism; subsequently improving student grades as well. Snyder et al. (2014) found that students who were exposed to a policy that punished excessive, unexcused absences had fewer absences than the control group who were simply provided a policy without reward or punishment. Furthermore, Hancock (1994) found substantially higher exam grades for the course sections where these punitive measures were employed. Moore and Jensen (2008) discovered similar findings regarding science lab sections, where the specter of a 7% drop in lab grade was sufficient to improve both the lab grade and overall course grade. This is, in part, to be expected, if students lose points for missing lab, then there is an obvious impact on final course grade. However, Moore and Jensen (2008) found that students who missed one lab, earned grades more than 10% lower than those who missed zero labs; meaning at least 3% of the grade differential was not explained by the policy. Furthermore, in their study, students who missed two labs earned grades “30-50% lower than students who missed no labs, and 20-30% lower than students who missed one lab” (p. 68). Once again, the detriment to their final grade was not fully explained by the punitive policy. In each of these instances, the compulsory attendance policy had the desired effect on student attendance and performance.

The other two tactics for curbing absenteeism are sparsely covered in research but may manifest more frequently in practice. An alternative punitive policy, which is more

subtle, is to draw exam questions from material solely covered in class (Lloyd et al. 1972). This strategy is supported by Marburger (2001) who recorded statistically, significant differences on correct answers to exam questions for those who attended a specific lecture, as opposed to those who missed. Although instructors may prefer punitive measures due to the “immediacy of the results” (p. 72), Beaulieu and Sheffler (1985) found no statistically significant differences when positive reinforcement was applied. Thus, rewarding students for regular attendance may be equally beneficial and perhaps appear less compulsory as the results are less immediate. These studies and others that evaluated the impact of mandatory attendance policies ($n = 1,421$) coalesced in Crede et al. (2010) and were shown to have a small, positive impact on academic performance ($d = .21$). Lin (2014) suggested faculty employ mandatory attendance policies in conjunction with complementary measures in the classroom like a daily quiz and drawing a substantial number of exam questions (25-30%) solely from lecture notes. Despite the evidence presented in these studies, and logical assumptions like Lin (2014) stated where “as long as student attendance improves, students will have a better chance of doing well on exams and receiving better grades” (p. 416), there remains staunch opposition, both in theory and in practice, to implementing such draconian policies.

Against Compulsory Attendance Policies. Detractors of compulsory attendance policies approach this conversation both in principle and empirically. St. Clair (1999) offers the most prominent, systematic admonishment of compulsory attendance policies in higher education. She stated, “a theoretical analysis is not only expected when empirical research is provided, but necessary when empirical research is equivocal” (p. 172). Using Pintrich’s (1994) theoretical model of motivation as the framework for her

argument, St. Clair (1999) suggested that mandatory attendance policies could inhibit student control, thereby discouraging student motivation for other academic behaviors. This becomes problematic as students who attend class to avoid the reprimand, instead of attending for the purpose of learning, may be physically present but not mentally engaged in the coursework. Sperber (2005) decried these very students, claiming they were a distraction and detracted from the overall character of the course. The focus of instructors therefore, should be to increase student motivation through boosting student self-concept, expectancy, and control. For example, Sperber (2005) explicitly stated in his syllabi that students would be graded under the assumption they had mastered the course content; if that could happen without attending class, then attending or not was the students' prerogative. It follows, students then choose to attend more frequently rendering a compulsory attendance policy moot.

St. Clair (1999) clarified, that compulsory attendance policies may not always be inappropriate. When external regulations (i.e., financial aid contingencies) require attendance or the composition of the class renders outside work insufficient (i.e., science labs or foreign language courses), then a mandatory policy may be appropriate.

Some strategies that have been used to encourage attendance, without out rightly requiring it, include daily participation points, instructor emphasis on the importance of attendance, and student sign-in sheets, all increased attendance and student engagement with the course. Moore (2005) compared two groups of students, one group who was issued a compulsory attendance policy and another where the instructor stressed the import for attending. The latter group was found to not only attend more frequently, but also earned higher grades. Another strategy employed by Liebler (2003) was the

incorporation of a daily quiz based upon the content of the course. Students attended class more regularly and were inherently prepared to engage in the content for the day.

Lastly, Shimoff and Catania (2001) recorded attendance among two comparative groups, one of which was asked to sign in for each class period. Those students in the control group-where students did not sign in-missed class 50% more than those who signed in. Not only did the experimental group attend more frequently, they also scored higher on weekly exams, including questions covered outside of class. Thus, the act of recording attendance, without directly requiring it, was satisfactory to improve attendance and student learning. These examples support the assertions of St. Clair (1999) that mandatory attendance may not be necessary if instructors, administrators, and academic support personnel can influence behavior through other mechanisms.

Attendance and Libertarian Paternalism. Based upon the opposing arguments of St. Clair (1999) and Lin (2014), it would appear there is little room for compromise. On one hand, St. Clair (1999) largely supported a libertarian view of attendance policy, one in which student and faculty ought to have the freedom of choice in their academic behavior. Given the current ‘Age of Accountability’ in higher education, Lin (2014) espoused more paternalistic policies, citing the body of literature that clearly demonstrates the impact of attendance on student performance. Thaler and Sunstein (2003) posited however, that the ideals of libertarianism and paternalism are not mutually exclusive. In their argument, Thaler and Sunstein (2003) acknowledged that people will inevitably, but not always, make inferior choices (e.g., skipping class) and that any entity (e.g., college or university) will inevitably make a choice that impacts the choices of others. Within the context of attendance, institutions cannot escape the fact that their

decision on an attendance policy will inevitably impact the choices of students; it would be incorrect, and arguably unethical to create a policy stating attendance does not matter. But the implied alternative is to compel attendance through policy that may be ineffective and assuredly undermines the academic freedoms of faculty and undergraduate scholars, alike. Neither, left to itself, appear to be a fully sufficient response and thus demand a compromise between the two.

This common ground can be found in emphasizing, monitoring, and communicating with students on their attendance behavior. Through the informed and intentional action of student affairs professionals, early-alert systems not only enhance communication between faculty, advisors, and students, but also interrupt disruptive behavior (Hudson, 2005). This is an important distinction, insofar that it does not deprive students of the freedom of choice for attending class, nor does it tangibly penalize students who can sufficiently glean course information via other learning strategies. By intervening with students before their behavior becomes substantially detrimental to their success, student behavior could be adjusted and fundamentally alter students' prospects for academic success. The early alert systems are largely dependent upon predictive models of student success, also referred to as predictive analytics.

Predictive analytics for student success are a rather new phenomenon, dating back to the late 1990s with Baylor University pioneering a "sophisticated admission strategy" (Campbell, DeBlois, & Oblinger, 2007, p. 44) that leveraged massive amounts of student data. Around a similar time, graduate students at the University of Alabama developed a predictive model for determining attrition risk. This model was comprised of an

assortment of eight variables, including cumulative grade point average, distance from home, and mathematics grades.

In Hudson (2005), student support professionals monitored the attendance of first year students enrolled in developmental coursework using an early-alert system. Faculty reported students with excessive absences at weeks 2, 4, and 6 of the semester to the academic advising office. Academic advisors subsequently contacted those students, with 85% of contacted students responding. The conversations with advisors helped facilitate students' reentry to class, where the fear of being stigmatized by excessive absences would otherwise have kept the student from returning to class (Hudson, 2005). Furthermore, in instances where chronic absenteeism was a precursor to student withdrawal, the outreach from advisors helped mitigate the readmit struggles for those students. Students even expressed surprise and amazement that "someone cared enough to contact them about their attendance" (p. 225).

Early alert interventions, even ostensibly simple ones, have been shown to be highly effective in reducing student risk. Of the students deemed *high risk* for not completing a course, 55% transitioned into a *moderate risk* category after the initial intervention and 25% moved from *high risk* to *low risk* (Arnold, 2010). Jayaprakash, Moody, Lauría, Regan, and Baron (2014) asserted that "simply making students aware that they are at risk of not completing a course motivates them to seek help and change their academic behaviour" (p. 12).

These sorts of models, however, do not come without a fair amount of skepticism, concern, and criticism. In an attempt to boost their retention rates, the president of Mount Saint Mary's University in Maryland, encouraged his faculty and advisors to compel

students who were likely to drop out, to do so prior to the census date and thus boost their retention rate by as much as 4-5% (Ekowo & Palmer, 2016). This sort of approach raised serious ethical concerns about the use of analytics in higher education. Because predictive models utilize historical data to determine risk, historically underserved populations are susceptible to systematic discrimination and stigmatization (Ekowo & Palmer, 2016).

Privacy concerns also abound when integrating big data analytics into student success. Along with the aforementioned concerns of discrimination, Rubel and Jones (2014) cited four other potential challenges with data and learning analytics. First, the imbalance of power between those who mine the data (schools) and those who provide the data (students). They contended that the information mined is of far more value to those collecting it, than any subsequent insights gained by the student. Furthermore, despite the aim of big data to increase transparency, the specific data mined for these models is often held in utter secrecy. Lastly, an unintended consequence of data mining is that it could create a *chilling effect*. They argued that when students become aware that their actions are being tracked, it inhibits their free expression and choice by wondering if and how their data may be used against them. In their response, Rubel and Jones (2014) presented four solutions that must be collectively addressed to proceed with the use of student data: (a) systems must be controlled to allow for differential access to private data, (b) specific justifications for specified data must be presented, (c) a full accounting must be rendered of how benefits of this data are “distributed between institutions and students, and among students” (p. 156), and (d) students should be presented reasonable choices pertaining to the collection and use of their data. In short, the mind of student

success professionals must be on ensuring students are not treated in a one-size fits all model, but rather values the student as an individual.

Georgia State University has demonstrated perhaps the greatest success of any school in its integration of data analytics for student success and could serve as a model for balancing the collective insights of predictive modeling while valuing the individual. Beginning in 2011, Georgia State University analyzed two and a half million student grades, subsequently generating a series of factors that contributed to these grades. Additionally, they hired 42 advisors to intervene with these students, using data to inform the nature of their conversations. The system spurred more than 43,000 personal interactions and led to a 22% increase in their graduation rates; essentially eliminating the achievement gap for at-risk students (Ekowo & Palmer, 2016).

Early alert systems provide perhaps the most equitable means to increase retention and student success, as the system does not deny access to education (Tinto, 2007). Tinto (2007) asserted that many schools attempt to increase their retention rates by limiting those who are admitted. Although his model did not account for those open access institutions and schools that are predicated on serving the under-served. Early alert systems can mitigate the risk of more underprepared students by providing just-in-time data to academic support personnel, who can subsequently provide just-in-time student support for these at-risk students. Boylan (2002) identifies attendance, specifically, as one of the criteria faculty and advisors should monitor in their early-alert systems. Further, Boylan (2002) suggests responsive interventions can include the advisement of behavior as well as support programs, like the campus day care center for students whose absenteeism is due to parental responsibilities. It is as Jayprakash et al.

(2014) stated, “predictive models do not influence course completion and retention rates without being combined with effective intervention strategies aimed at helping at-risk students succeed” (p. 8). Additionally, Kulik, Kulik, and Schwalb (1983) found evidence to support the notion that the success of these interventions is dependent upon them occurring as early as possible for students. It is incumbent upon student success professionals to incorporate effective strategies in risk intervention and academic success with these early alert functions informed by predictive analytic models.

In the ‘Age of Accountability’ and given the enrollment trends of higher education, an early alert system may be just the answer for the paradox facing many contemporary college administrators. By intervening with students at the appropriate time and providing timely information on their behavior, student support personnel can influence student success without employing compulsory measures that may undermine student choice. Although a proliferation of early alert systems have subsequently led to the establishment of successful intervention strategies, those factors have neglected to include student attendance data as a formative metric. Although schools cannot reasonably change factors like student first-generation status, gender, or high school grade point average, they can work to influence student behavior. Chief among these behaviors that impact student success, is attendance (Crede et al., 2010). Because attendance has the strongest relationship of any factor in predicting student success, it is imperative a model is established for intervening and correcting student attendance behavior. Thus the question remains, when does absenteeism reach the threshold for intervention? At what point do cumulative absences have a tangible, measurable impact

on student academic performance? The aim of this study is precisely to answer these questions.

CHAPTER III

METHOD

Classroom attendance is among the most foundational concepts in higher education. Not only is the basis for credit bearing courses predicated on the ‘credit hour’ – the amount of time spent in the classroom, but federal funding uses class attendance as the foundational metrics for verifying student enrollment. Perhaps it is because of this foundational nature of attendance that administrators, faculty, and students operate under the assumption of its relationship with student performance. The disparity among attendance policies, at both the institutional and classroom levels, suggests that the establishment of a threshold for recourse may not be firmly grounded in research. Furthermore, it is these assumptions that may explain the scarcity of literature demonstrating those thresholds for when absenteeism has a practically significant impact on student success.

Whereas some researchers have proposed either a *70% Rule* (Colby, 2004) or an *80% Rule* (Newman-Ford et al., 2008) as the trigger for intervention, both of these studies examined absences in strictly a summative review, by comparing student absences at the end of the semester to final grade. The absence of literature outlining the formative relationship between attendance and student success is problematic as faculty and student success professionals have no empirical basis for determining when, specifically, to intervene or establish precise thresholds for attendance policies. A formative measure of attendance risk regarding course outcome may provide the just-in-time data student success professionals need to successfully mitigate attendance risk.

The relationship between attendance and student success is so strong that faculty and staff ought to be operating from more than simple, nondescript assumptions.

The purpose of this non-experimental quantitative study was to examine the extent to which cumulative absences at specific points in the semester (Weeks 4, 8, 12, and 16) affect final course outcome at one small-to-mid-sized, private, religiously affiliated 4-year university in the Midwest United States. The primary independent variable was *cumulative absences* and the primary dependent variable measured was *final course outcome*. Both *course credits* and *weekly course sessions* were examined as potential confounding variables in the relationship between cumulative absences and final course outcome.

At the university under study, faculty are expected to record attendance for each student in each course they teach, using the institution's student information system (SIS), Banner. Absences, regardless of excused status, are to be coded within the SIS. Furthermore, courses at this university range from 1-credit to 4-credits; where each credit hour equates to 50 minutes of lecture-based classroom time. Consequently, a three credit course totals 2 hours and 30 minutes of weekly classroom time. This can be divided evenly into one of three potential offerings: (a) one, 2 hour and 30-minute class session each week, (b) two, 1 hour and 15-minute class sessions, or (c) three, 50-minute class sessions. This dynamic suggests one absence may have varying degrees of weight, depending on the duration of the class session missed.

Research Questions

The following questions were examined:

1. To what extent do the cumulative absences at week 4 relate to course outcome, accounting for the number of credit hours and sessions per week?
2. To what extent do the cumulative absences at week 8 relate to course outcome, accounting for the number of credit hours and sessions per week?
3. To what extent do the cumulative absences at week 12 relate to course outcome, accounting for the number of credit hours and sessions per week?
4. To what extent do the cumulative absences at week 16 relate to course outcome, accounting for the number of credit hours and sessions per week?
5. To what extent do the cumulative absences at week 4 relate to course outcome, when disaggregated by class standing?
6. To what extent do the cumulative absences at week 8 relate to course outcome, when disaggregated by class standing?
7. To what extent do the cumulative absences at week 12 relate to course outcome, when disaggregated by class standing?
8. To what extent do the cumulative absences at week 16 relate to course outcome, when disaggregated by class standing?

Design Overview

A quantitative non-experimental design was employed to determine the extent to which cumulative absences affect final course outcome, as well as the extent to which that impact is mitigated by number of credits and the number of weekly class sessions for a given course. These relationships were further disaggregated by student class standing (i.e., freshmen [0-29 completed credits], sophomore [30-59], junior [60-89], and senior [90+ completed credits]). Given that students' learning of course material does not

happen solely within the classroom, the nature of the relationship between absenteeism (as a measurement of behavior) and course-grade (as evidence of learning) simply does not allow for genuine control. Furthermore, because the dependent variable is course outcome, the potential results of requiring an experimental-population to be absent from class raises considerable ethical concerns. When these two acknowledgements are present, Johnson (2001) suggests a randomized experimental study is not possible.

Data Source

The intent of this study was to understand the relationship between attendance (independent variable) and final course outcome (dependent variable) with the intent to inform institutional attendance policy. In the same respect that academic policies apply equally regardless of student characteristics, this research was designed to decipher the relationship between attendance and course outcome irrespective of the myriad factors that influence student performance. Therefore, each student was treated as an individual participant for each of the courses for which they were enrolled in each semester. What this means, is that a student enrolled in five courses, was viewed as five individual participants, whereas a student enrolled in three courses, was considered three individual participants. Certainly, one could contest that higher caliber students would be more likely to enroll in a greater number of courses each semester and therefore bias the results towards higher caliber students. However, it is imperative to reiterate that academic policies, especially attendance policies, do not differ based upon student characteristics (e.g., credits enrolled, courses enrolled, HS GPA, prior term GPA).

The target population for this study was a convenience sampling of students enrolled in traditional undergraduate courses during the Fall and Spring semesters for

academic years 2015-2017, the only years in which attendance had been recorded in the student information system (Banner). In this context, *traditional* referred to the modality of the courses and not the student population. For the University, traditional represented face-to-face courses offered Monday through Friday and spanning a 16-week semester; students generally enrolled in multiple course concurrently. This was contrasted with the *accelerated* format of undergraduate courses where students enroll in one class at a time and study the same amount of content as traditional courses but spanning a period of six or eight weeks. This traditional, undergraduate population represented approximately 5,100 unique participants, with approximately 3,700 students enrolled each year. Of the unique participants, 66% were female ($n = 3,368$) and 34% were male ($n = 1,732$); 70.5% ($n = 3,597$) were enrolled full-time and 29.5% ($n = 1,502$) were enrolled part-time.

According to the 2017-2018 institutional census, 88% of students graduated high school in the top half of their class rank, with a mean high school grade point average for the population of 3.50. The 25th percentile for reported ACT Composite scores was 20 and the 75th percentile was 26, with 89% of reported scores falling within the range of 18-29.

Characteristics of Traditional Undergraduate Courses at the Research Site

The institution for which the sample was enrolled is a private, Christian, liberal arts university located in the Midwest United States. Undergraduate students were able to pursue academic programs in one of five academic colleges: Arts & Sciences, Business, Education, Health Professions, and Nursing. Programs within the School of Health Professions and the School of Nursing each required a Biological lab science, which means the offerings of Chemical and Physical lab sciences were generally limited.

Furthermore, as a private, Christian institution, students were required to complete at least three theology courses prior to graduation, irrespective of their religious affiliations.

Most lecture-based courses at this institution were 3-credit courses except for lab-sciences, which were 4-credits in total; the lab accounts for the additional credit. As such, students enrolled full-time were typically registered for four to six courses each semester and part-time students enrolled in three or less courses per semester. Thus, the 2,616 full-time students and 1,093 part-time students resulted in approximately 15,300 courses per term and subsequently 91,000 unique courses for which attendance was taken over the three-year period. The regularity with which faculty not only recorded attendance, but also transferred it to the SIS, had been inconsistent. Courses were removed from the study for courses where attendance was never taken or was only taken for the federally mandated first two weeks of the semester. Furthermore, participants for whom 20% or more of class attendance was not recorded were also removed. This is due to the findings of Newman-Ford et al. (2008) that identified 20% as the critical trigger for intervention and represented a 33% likelihood of course failure.

Procedure

This quantitative non-experimental study drew upon existing data from one private, Christian liberal arts university located in the northern Midwest United States. Before any data were collected, permission was sought through the Sam Houston State University Institutional Review Board. As part of the IRB process, permission to use this archival data was sought from the research site. Any identifiable student data was removed by the Office of Institutional Effectiveness-the office responsible for providing student data-prior to the researcher gaining access to the data.

All data used in this study was accessible by academic affairs professionals within the University, using the institution's SQL server reporting service (SSRS). Student-level data included individual course attendance records, midterm and final course outcome, student demographics-including race/ethnicity, gender, age, and class standing. Course descriptive information included subject code, course number, credit load, class sessions per week, and course type (e.g., lecture, lab, practicum). These data were presumed to be valid and reliable as recording attendance is required of faculty (Concordia University Wisconsin, 2018, p. 110)

Upon collection of these data, the raw data was aggregated to provide the independent variables necessary for answering the research questions. For example, whereas the raw data was presented as an individual row for each class session, of each course, for each student, these data were aggregated to represent the cumulative attendance rates at weeks 4, 8, 12, and 16 for each course, for each student. Furthermore, each class session was converted to number of minutes per session, so as to account for a greater amount of class missed in a class that meets one day a week for 2 hours and 30 minutes than a course that meets three times in a week, for 50 minutes per session. Understandably, the amount of class missed would be greater with the former and therefore more consequential, in theory, than one session missed in the latter situation.

Analysis

The proposed approach followed the process outlined by Cohen, Cohen, West, and Aiken (2002) who advocated for the use of regression whenever a researcher intends to explain a phenomenon. Their framework for causality, where one variable subsequently impacts another, necessitated the veracity of four observations: (a) temporal

precedence, (b) causal mechanism, (c) correlation, and (d) non-spuriousness. Each of these requirements have been met, either through logic or through previous literature.

First, *temporal precedence* is the establishment of one act preceding another. Within the relationship between attendance and final course outcome, this is obvious. The act of attending class can only happen during the timeframe for which a course is offered; a student could not attend a class session after that course has concluded for the semester. Similarly, a final course outcome can only be posted upon the conclusion of the course. Thus, a student could not attend a course session for a class in which the final grade had already been posted. Therefore, attendance logically precedes final course outcome.

Second, the *causal mechanism* posited within this study was that the independent variable (attendance) influences the dependent variable (final course outcome). Third, the *correlation* between attendance and course outcome is well established in the literature (e.g., Colby, 2004; Lin & Chen, 2006; Newman-Ford et al., 2008; Shimoff & Catania, 2001). The Unique Effects Model (Crede et al., 2010), whereby attendance and student characteristics “exert largely unique effects” (p. 275) on course performance demonstrated the *non-spuriousness* of attendance as a predictor of academic performance. With these requirements met, the use of regression is not only warranted, but necessary to partially explain the phenomenon of student success. To be clear, it is not altogether certain, nor intended, that this analysis will *prove* this causal model. However, it is intended that these data are consistent with the model provided. As Cohen et al. (2002) state, “the value of a given model is determined as much by the logic

underlying its structure as by the empirical demonstrations of the fit of a given set of data to the model.” (p. 65).

Statistical assumptions. A simple regression provides a measure of linear relationship between two continuous variables. A correlation is like a simple regression; however, the interest is in measuring the degree of relationship as opposed to predicting the dependent variable from the independent variable. The approach taken here is a correlation. Before running correlation analyses, the following statistical assumptions had to be assessed:

1. Continuous variables should be reasonably normally distributed.
2. Independence of observations – whereby one observation (e.g., attendance for student A) does not influence another observation (e.g., attendance for student B).
3. The third assumption is of homoscedasticity, or similar variances across each of dependent variables. This is generally represented using a scatter plot, where the plotted points are near equidistant from the line of best fit. Homoscedasticity is contrasted with heteroscedasticity where the variances differ across the data.

Effect size. As in all analysis, interest is centered not only on identifying a statistically significant relationship but in identifying the magnitude of the effect—the practical significance. In correlations, variance accounted for effect sizes, such as r^2 , will be reported.

Recognizing that class attendance has been presented as the most prescient indicator of student success, the identification of precise risk thresholds for absenteeism

is both cogent and necessary. In addition to understanding the relationship between attendance and final course grade, descriptive statistics will be used in exploring attendance thresholds for students who pass versus students who fail in order to allow for academic success intervention. By design, this study provided a logical and suitable approach for determining the intervention criteria. Because programs have varying grade point requirements and performance thresholds, these data may be most useful in demonstrating risk when the mean grade point average for each absence quantity approaches or falls below the required performance threshold.

CHAPTER IV

RESULTS

The purpose of this study was to identify the thresholds at which cumulative absences have a tangible and substantial impact on final course outcome. More precisely, the cumulative absences at weeks 4, 8, 12, and 16 of the semester were compared to final course outcomes to determine the extent to which cumulative absences predict final course grade. Because courses vary in both the number of credits (1-4) and the number of course sessions per week (1-5), these variables were accounted for in the analysis. Additionally, these relationships were further disaggregated by class standing (e.g., senior, junior, sophomore, freshmen).

Research Questions

The following questions were examined:

1. To what extent do the cumulative absences at week 4 relate to course outcome, accounting for the number of credit hours and sessions per week?
2. To what extent do the cumulative absences at week 8 relate to course outcome, accounting for the number of credit hours and sessions per week?
3. To what extent do the cumulative absences at week 12 relate to course outcome, accounting for the number of credit hours and sessions per week?
4. To what extent do the cumulative absences at week 16 relate to course outcome, accounting for the number of credit hours and sessions per week?
5. To what extent do the cumulative absences at week 4 relate to course outcome when disaggregated by class standing?

6. To what extent do the cumulative absences at week 8 relate to course outcome when disaggregated by class standing?

7. To what extent do the cumulative absences at week 12 relate to course outcome when disaggregated by class standing?

8. To what extent do the cumulative absences at week 16 relate to course outcome when disaggregated by class standing?

Hypotheses

The following null hypotheses were used to guide this study:

1. There will be no statistically significant relationship between *final course grade* by *cumulative absences* at week 4 of the semester.
2. There will be no statistically significant relationship between *final course grade* by *cumulative absences* at week 8 of the semester.
3. There will be no statistically significant relationship between *final course grade* by *cumulative absences* at week 12 of the semester.
4. There will be no statistically significant relationship between *final course grade* by *cumulative absences* at week 16 of the semester.
5. There will be no statistically significant difference across *class standing* in the relationship between *cumulative absences at week 4* and *final course grade*.
6. There will be no statistically significant difference across *class standing* in the relationship between *cumulative absences at week 8* and *final course grade*.
7. There will be no statistically significant difference across *class standing* in the relationship between *cumulative absences at week 12* and *final course grade*.

8. There will be no statistically significant difference across *class standing* in the relationship between *cumulative absences at week 16* and *final course grade*.

Data Source and Demographics

Archived data were collected from the student information system (SIS) at one small-to-mid-sized, private, Christian, 4-year Liberal Arts University in the Midwest United States. The data collected included: Term, Course Subject, Class Type, Course Credits, Class Sessions Per Week, Week 4 Absence total, Week 8 Absence total, Week 12 Absence total, Week 16 Absence total, Midterm Grade, Final Grade, Program (i.e., major), Class Standing, Race, Ethnicity, Gender, Age (years), Credits Earned Cumulative.

Other variables were calculated using the data already collected, those included: Minutes per Week (credits x 50 mins), Minutes per Session (Minutes per Week / Sessions per Week), Week 4 Total Minutes Missed (Week 4 Absence Total x Minutes per Session), Week 8 Total Minutes Missed (Week 8 Absence Total x Minutes per Session), Week 12 Total Minutes Missed (Week 12 Absence Total x Minutes per Session), Week 16 Total Minutes Missed (Week 16 Absence Total x Minutes per Session), Midterm Pass/Fail (where Pass \geq Midterm Grade of 2.0; fail \leq Midterm Grade of 2.0) and Final Pass/Fail (where Pass \geq Final Grade of 2.0; fail \leq Final Grade of 2.0).

In preparation for analysis, the string variables were converted to numeric characters. Those conversions included: Midterm Outcome (dichotomous, where Pass = 1, Fail = 0), Final Outcome (dichotomous, where Pass = 1, Fail = 0), Class Standing (Freshman = 1, Sophomore = 2, Junior = 3, Senior = 4), Ethnicity (Caucasian/White non-Hispanic = 1, African-American = 2, Hispanic/Other = 3, Asian = 4, American

Indian/Alaska Native = 5, Other = 6, Non Resident Alien = 7, Two or more races = 8, and Native Hawaiian/Pacific Island = 10), Gender (dichotomous, where Female = 1, Male = 0). Each *participant* was defined as one course, per student, per term, as most, if not all students enrolled in multiple courses, individual student counts are not equivalent to the *participant* count. Therefore, the collected data yielded 35,761 records comprised of 3,521 unique students over five semesters.

Although the impact of most demographic characteristics (e.g., race, ethnicity, gender, etc.) were not a specific focus of this research, the generalizability of these results is dependent upon an understanding of the participant demographics. Table 1 (below) displays the descriptive statistics across many of the salient demographic characteristics of this population, including Ethnicity, Gender, and Class Standing.

Furthermore, the composition of class structure, including course Credits and Sessions per Week, are both germane to the overall generalizability of these results. The descriptive statistics for these variables are listed within Table 2. Lastly, the discrepancies among grading thresholds across institutions may limit the generalizability of this model. The grade statistics for this sample skewed high ($M = 3.38$ $SD = 0.78$) suggesting either a preponderance of above average students or potential grade inflation. The frequencies are depicted in Table 3 and distribution in Figure 1.

Table 3

Participant Characteristics

Characteristic	Frequency	Percent
Ethnicity		
Not Provided	812	2.3%
African American	1105	3.1%
American Indian/Alaska Native	64	0.2%
Asian	668	1.9%
Caucasian/White non-Hispanic	30009	83.9%
Hispanic/Other	377	1.1%
Native Hawaiian/Pacific Island	73	0.2%
Non-Resident Alien	1313	3.7%
Other	88	0.2%
Two or more races	1230	3.4%
Unknown	22	0.1%
Gender		
Not Provided	812	2.3%
Female	20142	56.3%
Male	14807	41.4%
Class Standing		
Not Provided	812	2.3%
Freshman	10201	28.5%
Sophomore	8164	22.8%
Junior	7891	22.1%
Senior	8693	24.3%

Note. Unduplicated headcount ($n = 3,571$)

Table 4

Number of Participants Enrolled by Course Characteristic

Course Characteristic	Participants Enrolled	Percent
Course Credits		
1.00	2025	5.7%
2.00	295	0.8%
3.00	30241	84.6%
4.00	3200	8.9%
Minutes per Week		
50	2025	5.7%
100	295	0.8%
150	32563	91.1%
200	685	1.9%
250	193	0.5%
Sessions per Week		
1.00	5170	14.5%
2.00	16017	44.8%
3.00	14381	40.2%
5.00	193	0.5%
Minutes per Session		
50	16597	46.4%
70	677	1.9%
75	14547	40.7%
100	8	< 0.1%
150	4609	12.9%

Note. Unduplicated headcount ($n = 3,571$)

Table 5

Participants' Grade Distribution Across All Courses

Letter Grade	Grade Points	Frequency	Percent
A	4.00	15799	44.2%
A-	3.67	4788	13.4%
B+	3.33	3521	9.8%
B	3.00	4420	12.4%
B-	2.67	2243	6.3%
C+	2.33	1360	3.8%
C	2.00	1700	4.8%
C-	1.67	814	2.3%
D+	1.33	369	1.0%
D	1.00	452	1.3%
D-	0.67	215	0.6%
F	0.00	80	0.2%

Note. Unduplicated headcount ($n = 3,571$)

Research Question 1

The first research question addressed the extent to which cumulative absences at week four of the semester related to final course grade. At week four, less than one out of every four students had accumulated at least one absence (23.1%, $n = 7,910$). A descriptive analysis of student absences is outlined in Table 4 below. A Pearson r correlation was computed to assess the relationship between Week 4 Cumulative Absences and Final Course Grade. A weak, negative relationship was found between these two variables ($r = -.20$, $n = 34,161$, $p < .001$).

Table 6

Week 4 Absence Descriptives

Absences	Frequency	Percent	Pass	Fail	Pass Rate	Mean Final Grade
0	26251	76.8%	1102	25149	95.8%	3.43
1	5587	16.4%	452	5135	91.9%	3.19
2	1539	4.5%	222	1317	85.6%	2.91
3	508	1.5%	72	436	85.8%	2.87
4	166	0.5%	38	128	77.1%	2.59
5	65	0.2%	23	42	64.6%	2.41
≥ 6	45	0.1%	40	5	88.9%	2.99

Note. Unduplicated headcount ($n = 3,571$)

These results suggest that for each of the first five absences a student records prior to Week 4 of the semester, the proportion of students passing the course decreases by 6% ($M = -6.20$, $SD = 4.82$). Beyond five absences however, the impact varies drastically ($M = 0.40$, $SD = 48$). The sample size for students with greater than 5 absences is quite small ($n = 45$, 0.1%). Similar to the trend in pass rate reduction, the data suggests that each absence prior to Week 4—up to five absences—corresponds with final grade reduction close to two-tenths of a letter grade ($M = -0.19$, $SD = 0.14$). The change in pass rate and mean final grade between 2 and 3 absences was negligible. Beyond that however, each absence had a meaningful impact on student success. Students who amassed more than 5 absences, represented slightly more than one-tenth of one percent of the total sample size ($n = 45$, 0.13%). Exploring further, those data spanned myriad courses and subjects. Thus, these data may not be representative of the larger trend. To better describe the relationship between week four absences and final grade, a more granular analysis, disaggregated by course credits and sessions per week, is displayed in Table 5 below.

Table 7
Week 4 Absences and Final Course Grade Correlations by Credits and Sessions per Week

Credits	Sessions per Week	<i>n</i>	<i>r</i>	<i>p</i>
1	1	441	.12	< .001
	2	17	-.58	.02
2	1	143	-.06	.49
	2	149	-.10	.22
3	1	4083	-.10	< .01
	2	13942	-.22	< .01
	3	12189	-.20	< .01
4	1	383	-.27	< .01
	2	467	-.20	< .01
	3	2157	-.17	< .01
	5	190	-.15	.04

Note. Unduplicated headcount ($n = 3,571$)

A Pearson *r* correlation was calculated for Week 4 absences across each course credit value and further disaggregated by the number of course sessions per week. Corresponding with the aggregated correlation, all but one of the relationships were negative. The correlation between absences at week four and final grade was positive for 1 credit courses meeting once per week. However, for 1 credit courses that meet twice a week, a moderate, negative relationship was noticed. The sample size was extremely small ($n = 17$), in comparison to the overall sample ($n = 34,161$). Furthermore, neither of the correlations for two-credit courses were statistically significant.

Three credit courses meeting twice a week, for 75 minutes per session, demonstrated the strongest relationship among three credit courses ($r = -.22$ $n = 13,942$). The next strongest relationship was among those which met three times a week, for 50 minutes per session, where $r = -.20$. The weakest relationship among three-credit courses, was for those which met once a week—for 150 minutes—where $r = -.10$.

For four credit courses, a logical pattern in the magnitude of the correlations emerges. Because credit-hours are defined as 50 minutes per week per credit, it is to be expected that an absence in a course that meets less often for a greater amount of time, thus missing more minutes in a week, would be more consequential (i.e., represented by a stronger correlation). The Pearson r for four credit courses meeting once a week was $r = -.27$. Although a weak relationship, it was stronger than that for courses meeting twice a week ($r = -.20$), three times per week ($r = -.17$), as well as five times per week ($r = -.15$).

Research Question 2

The second research question addressed the extent to which cumulative absences at week eight of the semester, relate to final course grade. At the end of the eighth week, nearly four out of every 10 students had accumulated at least one absence (38%, $n = 12,980$). A descriptive analysis of student absences is outlined in Table 6 below. A Pearson r correlation was computed to assess the relationship between Week 8 Cumulative Absences and Final Course Grade. A weak, negative relationship was found between these two variables ($r = -.24$, $n = 34,161$, $p < .001$).

Table 8
Week 8 Absence Descriptives

Absences	Frequency	Percent	Pass	Fail	Pass Rate	Mean Final Grade
0	21181	62.0%	20420	761	96.4%	3.48
1	6726	19.7%	6321	405	94.0%	3.30
2	2899	8.5%	2648	251	91.3%	3.13
3	1550	4.5%	1383	167	89.2%	3.00
4	834	2.4%	711	123	85.3%	2.90
5	441	1.3%	352	89	79.8%	2.70
6	224	0.7%	175	49	78.1%	2.68
7	145	0.4%	113	32	77.9%	2.68
8	82	0.2%	66	16	80.5%	2.72
9	25	0.1%	14	11	56.0%	2.28
≥ 10	54	0.2%	44	10	81.5%	3.30

Note. Unduplicated headcount ($n = 3,571$)

Like the Week 4 results, a pattern emerges up to a given threshold. For Week 8 however, the threshold is at nine absences instead of five absences. This threshold was set based upon the drastic change in variability prior to- and after the threshold. For each of the first nine absences a student records prior to Week 8 of the semester, the proportion of students passing the course decreases by more than 4% ($M = -4.50$, $SD = 7.30$). Beyond the nine-absence threshold, the pass rate fluctuates ($M = 7.30$, $SD = 13.26$). However, as with the five-absence threshold in Week 4, the sample size for students with greater than nine absences at Week 8 is quite small ($n = 54$, 0.2%). The data suggests that each absence prior to Week 8—up to nine absences—corresponds with final grade reduction of more than one tenth of a letter grade ($M = -0.13$, $SD = 0.14$). The change in pass rate and mean final grade between 6 and 7 absences was negligible. For every other instance, within the threshold, each absence had a meaningful impact on student success. Students who amassed more than 9 absences, represented less than two-tenths of one percent of the total sample size ($n = 54$, 0.16%). As with the Week 4 data,

these 54 participants spanned a multitude of courses and subjects and therefore may not be representative of the larger trend. To better describe the relationship between Week 8 absences and final grade, a more precise analysis, disaggregated by course credits and sessions per week, is displayed in Table 7 below.

Table 9
Week 8 Absences and Final Course Grade Correlations by Credits and Sessions per Week

Credits	Sessions per Week	<i>n</i>	<i>r</i>	<i>p</i>
1	1	441	.11	.02
	2	17	-.53	.03
2	1	143	-.05	.59
	2	149	-.20	.01
3	1	4083	-.13	< .01
	2	13942	-.27	< .01
	3	12189	-.24	< .01
4	1	383	-.32	< .01
	2	467	-.25	< .01
	3	2157	-.22	< .01
	5	190	-.17	.02

Note. Unduplicated headcount ($n = 3,571$)

Pearson r correlations were calculated for the samples of Week 8 Absences, after disaggregating by both course credit value and by the number of course sessions per week. As with the Week 4 results, all but one of the relationships were negative. The correlation between absences at week eight and final grade was positive for 1 credit courses meeting once per week. However, for 1 credit courses that meet twice a week, a moderate, negative relationship was noticed. Once again, neither of the correlations for two-credit courses were statistically significant.

Three credit courses meeting twice a week, for 75 minutes per session, again demonstrated the strongest relationship ($r = -.27$, $n = 13,942$) among three-credit courses.

The next strongest relationship among three-credit courses was among those which met three times a week, for 50 minutes per session, where $r = -.24$. The weakest relationship among three-credit courses, was for those which met once a week—for 150 minutes—where $r = -.13$. All three of these correlations were stronger than they were at Week 4 of the semester, suggesting absence totals are a better indicator at the midpoint of the semester than at the end of the first quarter semester.

Once again, four credit courses follow the logical pattern whereby an absence is more detrimental in courses meeting less frequently for longer periods of time. The Pearson r for four credit courses meeting once a week was $r = -.32$. Although a weak relationship, it was stronger than that for courses meeting twice a week ($r = -.25$), three times per week ($r = -.22$), as well as five times per week ($r = -.17$). All four of the correlations were stronger than the same correlations at Week 4 of the semester.

Research Question 3

Research question 3 examined the extent to which cumulative absences at week twelve of the semester, related to final course grade. At the end of the twelfth week, nearly half of the students had accumulated at least one absence (46.6%, $n = 15,925$). A descriptive analysis of student absences is outlined in Table 8 below. A Pearson r correlation was computed to assess the relationship between Week 12 Cumulative Absences and Final Course Grade. A weak, negative relationship was found between these two variables ($r = -.27$, $n = 34,161$, $p < .001$). This relationship was stronger than at weeks eight and four.

Table 10

Week 12 Absence Descriptives

Absences	Frequency	Percent	Pass	Fail	Pass Rate	Mean Final Grade
0	18236	53.4%	17626	610	96.7%	3.50
1	6756	19.8%	6420	336	95.0%	3.37
2	3450	10.1%	3221	229	93.4%	3.26
3	1980	5.8%	1810	170	91.4%	3.11
4	1297	3.8%	1164	133	89.7%	2.98
5	812	2.4%	719	93	88.5%	2.97
6	533	1.6%	444	89	83.3%	2.79
7	373	1.1%	291	82	78.0%	2.72
8	259	0.8%	218	41	84.2%	2.75
9	149	0.4%	118	31	79.2%	2.69
10	115	0.3%	79	36	68.7%	2.48
11	75	0.2%	53	22	70.7%	2.50
12	37	0.1%	27	10	73.0%	2.57
13	33	0.1%	22	11	66.7%	2.36
14	21	0.1%	12	9	57.1%	2.02
15	14	0.0%	8	6	57.1%	1.91
≥ 16	21	0.1%	15	6	71.4%	3.37

Note. Unduplicated headcount ($n = 3,571$)

As with the previous research questions, a similar threshold materializes. For Week 12, the threshold appears at 14 absences. For each of the first fourteen absences a student records prior to the end of semester Week 12, the proportion of students passing the course decreases by nearly three percent ($M = -2.80$, $SD = 4.56$). The pass rate fluctuates greatly once the threshold is exceeded ($M = -6.30$, $SD = 40.80$). Once again, those exceeding the threshold represent a minute sample of the total population ($n = 35$, 0.1%), making it difficult to derive any reasonable generalizations. Furthermore, the data suggests that each absence prior to the end of Week 12—up to 14 absences—corresponds with final grade reduction of more than one tenth of a letter grade ($M = -0.11$, $SD = 0.11$). Interestingly, a slight increase in mean grade and pass rate were recorded at 8, 11, and 12 absences. For all other instances within the threshold of 14, each absence had a

meaningful impact on student success. To better describe the relationship between Week 12 absences and final grade, a more detailed analysis categorized by course credits and sessions per week, is displayed in Table 9 below.

Table 11

Week 12 Absences and Final Grade Correlations by Credits and Sessions per Week

Credits	Sessions per Week	<i>n</i>	<i>r</i>	<i>p</i>
1	1	441	.09	.07
	2	17	-.53	.03
2	1	143	-.02	.81
	2	149	-.27	.001
3	1	4083	-.17	< .01
	2	13942	-.31	< .01
	3	12189	-.28	< .01
4	1	383	-.36	< .01
	2	467	-.29	< .01
	3	2157	-.25	< .01
	5	190	-.25	.001

Note. Unduplicated headcount ($n = 3,571$)

A Pearson r correlation was calculated for Week 12 absences and final grade after disaggregating by both course credit value and by the number of course sessions per week. As with the Week 4 and Week 8 results, all but one of the relationships were negative. The correlation between absences at Week 12 and Final Grade was positive for 1 credit courses meeting once per week. However, for 1 credit courses that meet twice a week, a moderate, negative relationship was noticed. For the first time in this study, a correlation for two-credit courses was statistically significant. Those two-credit courses meeting twice a week, resulted in a negative, albeit weak, relationship ($r = -.27$, $n = 149$, $p = .001$).

Three credit courses meeting twice a week, for 75 minutes per session, again demonstrated the strongest relationship ($r = -.31$, $n = 13,942$) among three-credit courses. The next strongest relationship was among those which met three times a week, for 50 minutes per session, where $r = -.28$. The weakest relationship among three-credit courses, was for those which met once a week—for 150 minutes—where $r = -.17$. All three of these correlations were stronger than they were at Week 4 of the semester, suggesting they are a better indicator at the midpoint of the semester than at the end of the first quarter semester.

Four credit courses continue to follow the logical pattern whereby an absence is more detrimental in courses meeting less frequently, for longer periods of time. The Pearson r for four credit courses meeting once a week was $r = -.36$. Although a weak relationship, it was stronger than that for four-credit courses meeting twice a week ($r = -.29$) as well as those meeting three times per week and five times per week which were equal ($r = -.25$). All four of the correlations were stronger than the same correlations at Weeks 4 and 8 of the semester.

Research Question 4

The fourth research question examined the extent to which cumulative absences at week sixteen of the semester, relate to final course grade. At the end of the 16th week, more than half of the students had accumulated at least one absence (51%, $n = 17,367$). A descriptive analysis of student absences is outlined in Table 10 below. A Pearson r correlation was used to measure the relationship between Week 16 Cumulative Absences and Final Course Grade. A weak, negative relationship was found between these two

variables ($r = -.28$, $n = 34,161$, $p < .001$). This relationship was stronger than at each of the other three-time intervals.

Table 12

Week 16 Absence Descriptives

Absences	Frequency	Percent	Pass	Fail	Pass Rate	Mean Final Grade
0	16794	49.2%	16230	564	96.6%	3.50
1	6439	18.8%	6162	277	95.7%	3.41
2	3610	10.6%	3398	212	94.1%	3.30
3	2225	6.5%	2076	149	93.3%	3.20
4	1437	4.2%	1302	135	90.6%	3.10
5	1018	3.0%	928	90	91.2%	3.03
6	707	2.1%	611	96	86.4%	2.88
7	482	1.4%	402	80	83.4%	2.77
8	431	1.3%	362	69	84.0%	2.80
9	279	0.8%	228	51	81.7%	2.84
10	220	0.6%	178	42	80.9%	2.70
11	162	0.5%	127	35	78.4%	2.65
12	96	0.3%	65	31	67.7%	2.49
13	72	0.2%	51	21	70.8%	2.44
14	61	0.2%	42	19	68.9%	2.38
15	32	0.1%	22	10	68.8%	2.39
16	27	0.1%	18	9	66.7%	2.28
17	22	0.1%	17	5	77.3%	2.29
18	13	0.0%	7	6	53.8%	1.87
≥ 19	34	0.1%	21	13	61.8%	3.41

Note. Unduplicated headcount ($n = 3,571$)

Similar to the previous research questions, a pattern emerges for the first 16 absences. For each of the first sixteen absences a student records prior to the end of the semester (Week 16), the proportion of students passing the course decreases by approximately 2% ($M = -1.90$, $SD = 2.96$). Although the general trend for all absences is negative, the pass rate fluctuates greatly beyond 16 absences ($M = -4.20$, $SD = 16.46$). The number of participants exceeding the 16-absence mark represents only two-tenths of one percent of the total population ($n = 69$, 0.2%). The data suggests that each absence

prior to the end of Week 16—up to 16 absences—corresponds with final grade reduction of nearly one tenth of a letter grade ($M = -0.08$, $SD = 0.06$). Interestingly, the change in pass rate and change in mean grade did not entirely correspond; only at 8 absences did the data present an increase in both pass rate and mean final grade. Increases in pass rate occurred 5, 8, 13, and 17 absences. Increases in mean final grade occurred at 8, 9, and 15 absences; there was no change in mean grade from between 16 and 17 absences. For all other instances within the 16-absence threshold, each absence had a meaningful impact on student success. To better describe the relationship between Week 16 absences and final grade, a more detailed analysis categorized by course credits and sessions per week, is displayed in Table 11 below.

Table 13

Week 16 Absences and Final Grade Correlations by Credits and Sessions per Week

Credits	Sessions per Week	<i>n</i>	<i>r</i>	<i>P</i>
1	1	441	.13	.01
	2	17	-.53	.03
2	1	143	-.12	.15
	2	149	-.27	.001
3	1	4083	-.18	< .01
	2	13942	-.33	< .01
	3	12189	-.29	< .01
4	1	383	-.38	< .01
	2	467	-.32	< .01
	3	2157	-.26	< .01
	5	190	-.30	< .01

Note. Unduplicated headcount ($n = 3,571$)

A Pearson *r* correlation was calculated for Week 16 absences and final grade after sorting by both course credit value and by the number of course sessions per week. Once again, all but one of the relationships were negative. The correlation between absences at

Week 16 and Final Grade was positive for 1-credit courses meeting once per week. For 1-credit courses that meet twice a week, a moderate, negative relationship was observed ($r = -.53, n = 17, p = .03$). As with the Week 12 analysis, the correlation for two-credit courses meeting twice a week was statistically significant. Those two-credit courses meeting twice a week, recorded a weak, although slightly stronger, negative relationship ($r = -.27, n = 149, p = .001$).

Three credit courses meeting twice a week, for 75 minutes per session, again demonstrated the strongest relationship ($r = -.33, n = 13,942$) among three-credit courses. The next strongest relationship was among those which met three times a week, for 50 minutes per session, where $r = -.29$. The weakest relationship among three-credit courses, was for those which met once a week—for 150 minutes—where $r = -.18$. All three of these correlations were strongest at Week 16 of the semester.

For the first time, four credit courses did not strictly follow the logical pattern observed in research questions 1-3. The correlation was stronger for courses meeting 5 times a week ($r = -.31, n = 190, p < .01$). The Pearson r for four credit courses meeting once a week was $r = -.38$. Although a weak relationship, it was stronger than that for courses meeting twice a week ($r = -.32$) as well as those meeting three times per week ($r = -.26$). Like three-credit courses, all four of the correlations were strongest in comparison to the same correlations at Weeks 4, 8, and 12 of the semester.

Research Question 5

Research question 5 addressed the extent to which absences at Week 4 related to Final Course Outcome, when disaggregated by class standing. Table 12, below, displays the relationships where Final Course Outcome was defined as both *Final Grade* and

Pass/Fail. A Pearson r analysis was conducted to measure the relationship between absences and final grade. A point-biserial correlation was used to assess the relationship between absences and the dichotomous outcome of passing or failing a course. All eight correlations represented weak, negative relationships; each was statistically significant.

The strength of the correlation between Week 4 Attendance and Final Grade, from strongest to weakest, was Sophomore, Junior, Freshmen, and Senior. The strength of the correlation between Week 4 Attendance and Pass/Fail also followed the same trend: Sophomore, Junior, Freshmen, and Senior. Although maturation was listed as a potential threat to internal validity, under the presumption that students who made it to upperclassmen status were more likely to have established strategies for success, that threat is not supported by the data.

An online calculator for Fisher's r to z transformation (Lowry, 2019) was used to compute the z test statistic and compare between class standings. A one-tailed test was used for each of these comparisons. The differences between freshmen, sophomores, and juniors were not statistically significant. The difference in correlational coefficient for seniors was statistically significantly weaker than the rest of the group (e.g., between freshmen and seniors [$z = -2.08, p = .02$]). The difference in Pass/Fail correlations between freshmen and sophomores was statistically significant ($z = 2.61, p < .01$). The difference between sophomores and juniors was not statistically significant ($z = -1.91, p = .06$). These differences suggest more careful attention may need to be paid to sophomore absenteeism, as the impact of an absence is greater for them than any other class standing.

Table 14

Week 4 Correlations Between Absences and Final Course Grade and Course Outcome by Class Standing

Outcome Type	Class Standing	<i>n</i>	<i>r</i>	<i>P</i>
Final Grade	Freshmen (< 30 crs.)	9537	-.21	< .01
	Sophomore (30-59 crs.)	7739	-.23	< .01
	Junior (60-89 crs.)	7680	-.21	< .01
	Senior (≥ 90 crs.)	8434	-.18	< .01
Pass/Fail	Freshmen (< 30 crs.)	9537	-.13	< .01
	Sophomore (30-59 crs.)	7739	-.17	< .01
	Junior (60-89 crs.)	7680	-.14	< .01
	Senior (≥ 90 crs.)	8434	-.09	< .01

Note. Unduplicated headcount (*n* = 3,571)

Research Question 6

Research question 6 examined the extent to which absences at Week 8 related to Final Course Outcome, when disaggregated by class standing. Table 13, below, displays the relationships where Final Course Outcome was defined as both *Final Grade* and *Pass/Fail*. Pearson *r* analyses were conducted to measure the relationship between absences and final course grade. A point-biserial correlation was used to assess the relationship between absences and the dichotomous outcome of passing or failing a course. All eight correlations represented weak, negative relationships; each was statistically significant. Each correlation by class standing was stronger at Week 8 than Week 4.

The strength of correlation between Week 8 Attendance and Final Grade, from strongest to weakest, was Sophomore, Freshmen, Junior, and Senior. The strength of correlation between Week 8 Attendance and Pass/Fail also followed the same order: Sophomore, Freshmen, Junior, and Senior. Insofar that the relationships for juniors and

seniors was weaker than for underclassmen (i.e., freshmen and sophomores), the data suggests the threat of maturation may be plausible.

An online calculator for Fisher's r to z transformation (Lowry, 2019) was used to compute the z test statistic and compare between class standings. A one-tailed test was used for each of these comparisons. The only difference in Final Grade correlations that was statistically significant was between juniors and seniors ($z = -3.2, p = .001$).

Regarding Pass/Fail correlations, the difference between freshmen and sophomores was not statistically significant ($z = 1.76, p = .07$). The other differences were statistically significant: sophomores and juniors ($z = -2.69, p = .007$); juniors and seniors ($z = -3.93, p < .001$). Therefore, the data at Week 8 suggest upperclassmen are less affected by the impact of an absence.

Table 15

Week 8 Correlations Between Absences and Final Course Grade and Course Outcome by Class Standing

Outcome Type	Class Standing	n	r	p
Final Grade	Freshmen (< 30 crs.)	9537	-.26	< .01
	Sophomore (30-59 crs.)	7739	-.27	< .01
	Junior (60-89 crs.)	7680	-.24	< .01
	Senior (≥ 90 crs.)	8434	-.20	< .01
Pass/Fail	Freshmen (< 30 crs.)	9537	-.17	< .01
	Sophomore (30-59 crs.)	7739	-.20	< .01
	Junior (60-89 crs.)	7680	-.16	< .01
	Senior (≥ 90 crs.)	8434	-.10	< .01

Note. Unduplicated headcount ($n = 3,571$)

Research Question 7

Research question 7 explored the relationship between Week 12 cumulative absences and Final Course Outcome, when disaggregated by class standing. Table 14, below, displays the relationships where Final Course Outcome was defined as both *Final*

Grade and Pass/Fail. Pearson r analyses were conducted to measure the relationship between absences and final course grade. A point-biserial correlation was used to assess the relationship between absences and the dichotomous outcome of passing or failing a course. All eight correlations represented weak, negative relationships; each was statistically significant. Each correlation by class standing was stronger at Week 12 than Week 8.

The strength of correlation between Week 8 Attendance and Final Grade, from strongest relationship to weakest, was Sophomore, Freshmen, Junior, and Senior. The strength of correlation between Week 12 Attendance and Pass/Fail also followed the same order: Sophomore, Freshmen, Junior, and Senior. Similar to the results at Week 4 and Week 8, the data suggests the threat of maturation may be plausible, at least to the extent that the relationships were stronger for underclassmen than upperclassmen.

An online calculator for Fisher's r to z transformation (Lowry, 2019) was used to compute the z test statistic and compare between class standings. A one-tailed test was used for each of these comparisons. The only difference in Final Grade correlations that was statistically significant was between juniors and seniors ($z = -2.44, p = .01$). This difference was smaller than the same comparison at Week 8. In terms of Pass/Fail correlations, the only difference that was not statistically significant was between freshmen and sophomores. The other differences were statistically significant: sophomores and juniors ($z = -2.32, p = .02$); juniors and seniors ($z = -3.18, p < .001$). Each of the differences between class standings were smaller than they were at Week 8. Although the data at Week 12 suggests upperclassmen are still less affected by the impact of an absence than underclassmen, that differential is closing.

Table 16
Week 12 Correlations Between Absences and Final Course Grade and Course Outcome by Class Standing

Outcome Type	Class Standing	<i>n</i>	<i>r</i>	<i>p</i>
Final Grade	Freshmen (< 30 crs.)	9537	-.28	< .01
	Sophomore (30-59 crs.)	7739	-.29	< .01
	Junior (60-89 crs.)	7680	-.27	< .01
	Senior (≥ 90 crs.)	8434	-.23	< .01
Pass/Fail	Freshmen (< 30 crs.)	9537	-.19	< .01
	Sophomore (30-59 crs.)	7739	-.21	< .01
	Junior (60-89 crs.)	7680	-.18	< .01
	Senior (≥ 90 crs.)	8434	-.13	< .01

Note. Unduplicated headcount (*n* = 3,571)

Research Question 8

Research question 8 explored the relationship between Week 16 cumulative absences and Final Course Outcome, when disaggregated by class standing. Table 15, below, displays the relationships where Final Course Outcome was defined as both *Final Grade* and *Pass/Fail*. Pearson *r* analyses were conducted to measure the relationship between absences and final course grade. A point-biserial correlation was used to assess the relationship between absences and the dichotomous outcome of passing or failing a course. All eight correlations represented weak, negative relationships; each was statistically significant. Each correlation by class standing was stronger at Week 16 than Week 12.

The strength of correlation between Week 16 Attendance and Final Grade, from strongest relationship to weakest, was Sophomore, Freshmen, Junior, and Senior. However, the difference between sophomores and freshmen was rather miniscule. The for strength of correlation between Week 16 Attendance and Pass/Fail also followed the same order: Sophomore, Freshmen, Junior, and Senior. As with the results from the other

time intervals, the data suggests the threat of maturation may be plausible, insofar that the relationships were stronger for students with less than 60 credits than those with more than 60 credits.

An online calculator for Fisher's r to z transformation (Lowry, 2019) was used to compute the z test statistic and compare between class standings. A one-tailed test was used for each of these comparisons. The lowest p value was for the difference in Final Grade correlations was between juniors and seniors ($z = -1.91, p = .06$). This difference was considerably smaller than the same comparisons at Weeks 4, 8, and 12. However, this difference was not statistically significant. With regards to Pass/Fail correlations, the only difference that was statistically significant was between juniors and seniors ($z = -2.8, p < .01$). The other differences were not statistically significant. This includes, for the first time, the difference between sophomores and juniors. The differential between class standings continued to close from Week 12 to Week 16.

Table 17
Week 16 Correlations Between Absences and Final Course Grade and Course Outcome by Class Standing

Outcome Type	Class Standing	<i>n</i>	<i>r</i>	<i>P</i>
Final Grade	Freshmen (< 30 crs.)	9537	-.29	< .01
	Sophomore (30-59 crs.)	7739	-.29	< .01
	Junior (60-89 crs.)	7680	-.28	< .01
	Senior (\geq 90 crs.)	8434	-.25	< .01
Pass/Fail	Freshmen (< 30 crs.)	9537	-.20	< .01
	Sophomore (30-59 crs.)	7739	-.21	< .01
	Junior (60-89 crs.)	7680	-.19	< .01
	Senior (\geq 90 crs.)	8434	-.14	< .01

Note. Unduplicated headcount ($n = 3,571$)

Conclusion

The purpose of this study was to identify the thresholds for when cumulative absences have a tangible and substantial impact on final course outcome, specifically at the time intervals of Weeks 4, 8, 12, and 16. Although the results did not necessarily elucidate a precise moment for intervention, the results from these eight research questions provide valuable context to inform the timely intervention for students. Some general trends, within given thresholds, did emerge. Many of these followed logical expectations, whereas others defied expectations.

Research questions one through four explored the relationship between cumulative absences at given time intervals (i.e., weeks 4, 8, 12, and 16) and final course outcome (i.e., final grade and pass rate). Each accumulated absence, up to a certain threshold, corresponded with a drop in the pass rate ranging from a 6% when measured at Week 4 to 2% when measured at Week 16. Similarly, the per absence decrease in final grade average ranged from -.2 at Week 4 to -.08 at Week 16. It was also expected that an absence in courses meeting less frequently for longer periods of time would be more

problematic—because they would be missing a greater proportion of class, in terms of minutes missed. However, the data did not necessarily follow the expected pattern for 1-, 2-, or 3-credit courses. Generally, it followed that pattern for 4-credit courses.

Research questions five through eight explored the same question, but disaggregated the results based upon class standing. Across all four time intervals, the relationship for sophomores was stronger than their peers, often statistically significantly so. For weeks 8-16, seniors displayed the weakest relationship between absences and final course outcomes, followed then by juniors. This affirms the plausibility that maturation mitigates the relationship between absenteeism and course performance. As with questions one through four, the absence-performance correlations for each class standing strengthened throughout the semester. The correlations were strongest at Week 16, followed by Week 12, then Week 8, and Week 4, respectively. The relationships for seniors, especially early in the semester, was virtually non-existent. At Week 4, for instance, the relationship between absences and course outcome was as low as $-.09$. The implications of these results are discussed in Chapter 5.

CHAPTER V

DISCUSSION

This study sought to understand the impact of absenteeism on student success, specifically for those moments when the effects of absenteeism become irreversible so student success personnel can more intentionally intervene. The purpose of this study was to identify the thresholds for when cumulative absences have a tangible and substantial impact on final course outcome (both final grade and pass/fail). Although there was not a defining moment when the scales of student success tipped and all hope of passing was lost, the results suggested that each absence does have a meaningful impact on both final course grade and the proportion of students who fail the course. In most instances, the relationship between cumulative absences and course outcome was negative. These results strengthened over time, where the later time intervals provided stronger relationships than the earlier weeks. Furthermore, the impact of absenteeism generally appeared to be greater for underclassmen (those with less than 60 credits) than it was for upperclassmen. Findings for each of the eight research questions are discussed more specifically in the following paragraphs. The implications of these results are then subsequently discussed.

The first hypothesis was that there would be no statistically significant relationship between *final course grade* and *cumulative absences* at Week 4 of the semester. In fact, a statistically significant, negative relationship between Week 4 cumulative absences and final grade materialized. This relationship was rather weak ($r = -.20$). However, a pattern emerged for the first five absences, where each absence corresponded with a decrease in mean grade point average of .19. Similarly, a mean

average of 6% more students failed the course with each additional absence accrued. Students who missed more than five absences experienced varying degrees of success—where some absence totals recorded higher mean grade point averages and pass rates than others. Because these results were similarly discovered at each time interval, the reasoning for these findings is discussed later in this section. Based on these results, it is appropriate to reject the null hypothesis. It is therefore encouraged that absences be monitored at Week 4 of the semester and considered as a potential metric for intervention.

The second hypothesis was that there would be no statistically significant relationship between *final course grade* and *cumulative absences* at Week 8 of the semester. As with the first null hypothesis, this one too can be rejected. The relationship between final course grade and Week 8 cumulative absences was statistically significantly negative ($r = -.24$). Although still weak, this relationship was stronger than it was at the Week 4 interval. Interestingly, the impact of cumulative absences diminishes over time. Whereas at Week 4 each additional absence corresponded with a 6% decrease in the proportion of students passing and a .19 drop in mean grade point average, the Week 8 absences corresponded with a 4% decrease in the proportion of students passing and a decrease in mean grade point average of .13. This trend was only observed up through the first nine absences of the semester. The performance of students who accrued greater than nine absences by Week 8 fluctuated greatly. Some absence totals corresponded with higher pass rates and mean grade point averages; others recorded poorer performances.

The third hypothesis postulated that there would be no statistically significant relationship between *final course grade* and *cumulative absences* at Week 12 of the semester. The relationship between these two variables was statistically, significantly negative ($r = -.27$). Once again, this relationship was stronger than at weeks four and eight, but the impact of each absence was smaller. For each absence recorded in the first 12 weeks of the semester, students failed the course at a proportion nearly 3% greater and experienced a mean grade point average drop of .11. The null hypothesis is therefore rejected. As with the first two research questions, these results followed a pattern only up to a certain threshold. In the case of Week 12 cumulative absences, the threshold where performance deviated from the preceding trend, was upon accruing 14 or more absences. These students experienced varying degrees of success that did not follow a specific pattern. With these results in mind, student success personnel should continue monitoring and subsequently responding to student absenteeism up to the twelfth week of the semester.

The fourth hypothesis anticipated that there would be no statistically significant relationship between *final course grade* and *cumulative absences* at week 16 of the semester. This null hypothesis is rejected, as the results returned a statistically significant, negative relationship ($r = -.28$). This is the strongest relationship among the four time intervals. Once again, however, the impact of each absence was slightly less than the preceding time interval. Each absence corresponded with a 2% greater proportion of students failing and a decrease in mean grade point average of .08. The threshold for which the impact of each absence diverges is found at the 16th absence. Beyond sixteen absences, student performance fluctuates with each additional absence.

Because of these results, it is altogether appropriate, and suggested, that student attendance be monitored throughout the entire semester.

The two prevailing trends found through the first four research questions are that (a) each absence accrued corresponds with a meaningful drop in the proportion of student passing the course and the mean grade point average and (b) that these patterns hold true only to a given threshold. This threshold is reached once the number of absences exceeds the rate of one absence per week. At week four the threshold was five absences; week eight was nine absences, week twelve was fourteen absences, and week sixteen was sixteen absences. To be clear, the proportions of students who exceed these thresholds are quite small. The proportions of students exceeding those thresholds ranged from one-tenth of one percent to two-tenths of one percent. These proportions are so small, that it is difficult to draw any reasonable generalizations from these patterns. However, because the pattern threshold is found in each of the four time intervals, it does beg the question if there may be a rational explanation for this divergence. This departure from the preceding patterns may be explained by either or both of two primary explanations. First, some students may be able to perform strongly irrespective of their attendance patterns. Those who have developed stronger autonomous learning strategies may be able to overcome the adverse effects of absenteeism. Second, the University policy at the research site stated that once a student reaches either six consecutive absences or ten intermittent absences in a semester, the instructor has the prerogative to drop the student from the course—referred to as an *administrative withdraw*. Consequently, if faculty follow this policy, there could be a preponderance of students who were administratively withdrawn from the course and therefore not included in this data set. Perhaps then, the only

students who were allowed to stay in the course—and thus represented in the dataset—were those students who were performing strongly at the point in which they could have otherwise been dropped.

It is also worth noting that the expected pattern that absences in courses meeting less frequently, for longer durations, would be more detrimental did not necessarily manifest. For one-credit courses, a positive relationship was found for courses meeting once a week. Although the results were not statistically significant, the fact that this relationship was positive at all four time intervals is intriguing, especially considering that the one-credit courses meeting twice a week—for half as long as those meeting once a week—returned a negative relationship. The sample size was extremely small ($n = 17$) making it unreasonable to draw any generalizations from this pattern.

For two-credit courses, those meeting once a week had essentially no meaningful relationship, with Pearson r -values ranging from $-.02$ (week 12) to $-.12$ (week 16). Two credit courses meeting twice a week recorded a stronger, albeit still weak, relationship. Even though the sample size was rather moderate ($n = 149$), these relationships were statistically significant at weeks 8, 12, and 16. This pattern suggests that an absence in a two-credit course meeting twice a week is more consequential than an absence in a two-credit course meeting once a week—for twice as long as the two-credit courses. This is opposite of the expectation that longer sessions would be more consequential because they were missing ‘more class’ over the duration of the semester. This expectation did not bear truth from these data.

The course type with the greatest enrollment was three-credit courses ($n = 30,214$). Yet, similar to two-credit courses, the expected pattern did not materialize. The

strongest relationships among three-credit courses was consistently among those which met twice a week. Even the courses that met three times per week, for 50 minutes per session, recorded a stronger relationship than the three-credit courses meeting only once per week, for 150 minutes.

Four-credit courses were the first, and only, to follow the logical pattern whereby an absence in courses meeting less frequently, for longer durations, would be more consequential than the courses meeting more frequently, for shorter durations. The two strongest negative relationships between absences and final grade were with four-credit courses meeting once per week, at weeks twelve ($r = -.36$) and sixteen ($r = -.38$). Four-credit courses meeting twice per week returned the next strongest relationships between absences and final grade. Accordingly, those courses meeting three times per week recorded generally stronger relationships than those meeting five times per week. The only exception came in Week 12, when both r -values were the same ($r = -.25$) and Week 16, when the 5-sessions per week recorded a stronger r -value ($r = -.31$) than 3-session courses ($r = -.26$). The courses meeting were generally lab-science courses, higher level mathematics courses, and foreign language courses. This aligns with St. Clair (1999) who, in her admonishment of compulsory attendance policies, suggested they may be appropriate when outside work is largely insufficient—citing lab sciences and foreign language courses as two examples of potential exceptions. In short, the data suggests that absences are generally more consequential in higher credit-bearing courses.

Hypothesis five stated there would be no statistically significant difference across *class standing* in the relationship between *cumulative absences at week 4* and *final course grade*. Interestingly, there was a statistically significant difference in the correlation

coefficients between Seniors and Freshmen—whose Week 4 absence and final course grade correlations were the weakest among all four class standings. The differences between freshmen, sophomores, and juniors were not statistically significantly different, in terms of the relationship between attendance and final course grade. There was a statistically significant difference in pass rates between freshmen and sophomores, where sophomores were more impacted by each absence than freshmen. Perhaps it is due to an overconfidence bias by sophomores, or perhaps sophomores are generally enrolled in more rigorous courses. Regardless, the fact that each absence is more detrimental to sophomores than freshmen is noteworthy. Based upon these results, the null hypothesis was rejected. As was to be expected, Seniors returned the weakest relationship between absences and final course grade, suggesting the effects of maturation are plausible. If upperclassmen have developed the self-regulation and autonomous learning strategies over the preceding two to three years, perhaps that is enough to largely overcome any impediments caused by absent behavior.

For hypothesis six, it was posited that there would be no statistically significant difference across *class standing* in the relationship between *cumulative absences at week 8* and *final course grade*. Once again, the strongest correlation for this relationship was with Sophomores. However, unlike at Week 4, Freshmen demonstrated the second strongest relationship. These two correlations were not statistically significantly different from each other, nor were they from the correlation for Juniors. However, the difference for Seniors was statistically significantly different from Juniors. With regards to the pass/fail proportions for the four class standings, the differences were statistically significantly different between freshmen and juniors as well as juniors and seniors.

These differences reinforce the plausibility of maturation impacting the relationship between absenteeism and course outcome. Because of these statistically significant differences, the null hypothesis was rejected.

The seventh hypothesis stated that there would be no statistically significant difference across *class standing* in the relationship between *cumulative absences at week 12* and *final course grade*. Like the Week 4 and Week 8 relationships, Sophomores continued to be most strongly impacted by the effects of absenteeism. For both course outcomes, those with less than 60 credits (Sophomores and Freshmen) had stronger relationships between attendance and course outcome than the upperclassmen. The difference in course outcome correlations for both final grade and pass/fail was statistically significant between Juniors and Seniors. Further, the difference in correlations with pass/fail as the dependent variable were statistically significant between Sophomores and Juniors, but not Sophomores and Freshmen. Because many of the differences were statistically significant, the seventh hypothesis is rejected. The implications of this prevailing trend are discussed later in this chapter.

The eighth and final hypothesis stated that there would be no statistically significant difference across *class standing* in the relationship between *cumulative absences at week 16* and *final course grade*. Interestingly, and for the first time in this analysis, the results did not reject the hypothesis. The most noteworthy difference in the correlation coefficients was between Sophomores and Juniors, where $p = .06$; yet, that did not meet the established level for statistical significance ($p = .05$). Perhaps, as a summative metric, the impact of absenteeism effects students relatively the same, irrespective of class standing. If this is the case, which these data suggest, it is worth

considering whether *class standing* impacts the effectiveness of early alert interventions. This is due to there being a noticeable and statistically significant difference in the impact of absences between upperclassmen and underclassmen earlier in the semester, despite the relationships at the end of the semester being relatively similar. If it is as Arnold (2010) found, that interventions can mitigate risk, perhaps underclassmen benefitted most from interventions helping student design strategies to overcome this missed work. Plausibly, seniors already understood their specific strategies to overcome the ill-effects of absenteeism so would not be as impacted early in the semester to change their academic behaviors.

Implications

Although the correlations throughout these results were rather weak, there remain considerable practical implications for how these results inform the practices of students, advisors, faculty, and administration. First, the mere fact that the relationships were generally positively correlated, save for 1-credit courses meeting once a week, strongly supports the notion of attending class. If class attendance is to be encouraged by administration, advisors, and faculty, it then follows that attendance ought to also be recorded because the student perception that their faculty “doesn’t notice or care that I am there” (Friedman, Rodriguez, & McComb, 2001) clearly influences the decision to attend or not. Logically, if attendance is then to be recorded, the recording of attendance should be monitored by administration. The ‘Accountability Triangle’ has a trickle-down effect, where faculty must be accountable to institutional leadership, as the institution is accountable to both students and the government (Burke, 2005).

Second, the increased strength in correlations throughout the semester—where weeks 8, 12, and 16 were stronger than the preceding weeks—demonstrates the impetus for continuing to monitor attendance, irrespective of federal legislative policies (i.e., federal census requirements). For students who accumulated four absences at the first checkpoint (Week 4) they earned a mean final grade of ($M = 2.59$). At Weeks 8, 12, and 16, those with four absences earned mean final grades of $M_{wk\ 8} = 2.90$, $M_{wk\ 12} = 2.98$, $M_{wk\ 16} = 3.10$, respectively. It is therefore plausible that ceasing to miss any more class results in an increase in final grade. Just as Li and Chen (2006) noted, the effects of absences demonstrate a compounding, or *cumulative effect*, throughout the semester. A further analysis is needed to determine more precisely the potential change in students who remediate their absent behavior, but the data bolsters Jayaprakash et al. (2014) who encouraged informing students of the impending peril in order to influence a change in student behavior.

With regard to divergent policies based upon various course or student characteristics, the relative similarity in correlational strength across the credit-bearing spectrum (1-4 credit courses) suggests that one policy is sufficient, at least from an institutional perspective. Certainly, the course structure for any particular course—and therefore any particular credit-weight—would need to consider the other instructional design elements, at the discretion and prerogative of the individual instructor. However, the idea that an institution would employ a separate attendance policy for two-credit courses than for four-credit courses, is not supported by these data. The prevailing trend of maturation, insofar that Seniors (90+ credits earned) were statistically significantly less impacted by each absence than underclassmen, raises the question of a different policy

based upon student characteristics. From a practical standpoint, this appears difficult to equitably execute. For this particular research site, most upper-level courses had comingled enrollments. It was plausible that Freshmen and Seniors could be enrolled in the same class; Juniors and Seniors were almost certainly enrolled in many of the same courses. As such, a stated policy that discriminated based upon class standing and therefore likely age, is impractical to say the least. Further, although the difference was statistically significant, directionally absences were still negatively correlated with final grade for all class standings. Even if the impact was smaller, the faculty would not be wrong to enforce attendance policies for Seniors; these data suggest it would not be counterproductive.

As it relates to Sophomores, however, the recurring pattern whereby Sophomores were most impacted by the effects of each absence suggests attendance needs to be especially emphasized to this population of students. For those schools which have an established Second-Year Experience, it is suggested a lesson or topic of conversation be devoted to emphasizing the importance of attending class. Certainly, students may feel as if they have established the proper study habits to no longer need the paternalistic policies they required as freshmen, the data suggests otherwise. Whether it is the overconfidence bias that comes from a year of experience or an underappreciated increase in academic rigor for higher level (sophomore level) courses, it is apparent that specific attention needs to be devoted to students within the 30-59 completed credit range.

For advisors, the implications of the threshold for when the pattern diverges raises more questions than answers. At the point in which a student has accumulated more absences than there have been weeks of class (e.g., 5 absences at the conclusion of Week

4), the student success advisor should reach out directly to the instructor to gather more information as to the viability of that student succeeding in the course. As an ‘early-alert’ the prevalence of absences draws considerable attention for any student success professional and provides tangible evidence for the impact that would likely have on a student’s final course outcome. The review of literature in this study did not offer any evidence that excessive communication or interactions with an advisor would be detrimental. As such, the only burden of early-alert outreach would be on the staff. The general trend provides clear indicators for how to best prioritize that student outreach. Students who have amassed the greatest amount of absences within the given threshold for that particular week, should be among the first to receive outreach. Although these data are compelling, it is not advised that the data be flippantly shared. Instead, the context and narrative that surrounds this data should be communicated in a way that encourages students to change their behavior. If these data were simply shared without proper explanation, it may become a self-fulfilling prophecy for students, thus eradicating the benefits an early alert could have on student success.

Limitations

This research is limited in a few prominent ways. First, the extreme ethnic homogeneity detracts from the generalizability to any schools with a more ethnically diverse student body. It is not suggested that schools have different academic policies across various ethnicities, or any particular demographic for that matter, but the impact of absenteeism may differ for a more diverse student sample. Also, the high performance of the population, with a mean grade point average of 3.38, may not be characteristic of other institutions. With a population that is performing at a mean average of greater than

a B+, this population may be more or less impacted by absenteeism. Next, because this research only considered students who were enrolled for the entire semester, those students who withdrew or were dropped from their courses (whether due to excessive absences or otherwise) were not considered. If these students chose to withdraw from the course because they had amassed too many absences to catch up on content, these results could have changed the attendance patterns in meaningful ways. Lastly, the fact that the reliability of these data are subject to human data integrity interjects a potential confounding variable. Catania and Shimoff (2001) found that the act of recording attendance was enough to compel students to attend more. Because these data only considered the attendance patterns and course performance for students enrolled in courses where the faculty recorded attendance, it limits the results by excluding the impact of absenteeism on students who enrolled in courses where attendance was not recorded. The impact of absenteeism logically exists irrespective of faculty recording attendance. However, the extent of that impact is unknown.

Direction for Further Research

Because of these limitations, it is encouraged that scholars undertake efforts to fill in the gaps. A more extensive study should consider the myriad factors that influence student success (affective, behavioral, cognitive, and demographic) in conjunction with attendance (also a behavior). This analysis could potentially help explain or refute the prospect of maturation and its influence on the impact of absenteeism and course outcome. Second, future studies should consider including withdraw and drop counts as additional course outcomes. On one hand, a withdraw is not as negatively consequential as failing a course. On the other however, it is not a successful completion of the course.

This examination may increase the number of students who amassed a large quantity of absences throughout the semester, potentially bringing more consistency in the results. Next, researchers should consider other mechanisms for recording attendance. If these mechanisms happen either with or without the knowledge of students, perhaps it can fill the knowledge gap where this research was exclusive reliant upon faculty recording attendance.

Because the impact of an absence was not always more negative for one-session-per-week courses than for those courses meeting two or three class sessions per week, an examination of the instructional design elements ought to be undertaken. If the one-session-per-week courses generally employed a ‘flipped-classroom’ instructional method and were grades were heavily test-dependent, but courses meeting multiple times per week were more lecture dependent, that could explain the pattern that emerged contrary to the logical hypothesis. Lastly, a more extensive review of individual student behavior should be undertaken to determine the impact of intervention on student behavior and subsequent performance. If, for instance, a student acquires four absences at Week 4, but then never misses again, how does their final course outcome differ from someone who only missed one at Week 4 and three more throughout the semester? If two students each miss 4 absences prior to Week 4, one of whom alters their behavior and the other does not, what differences emerge in their behavior and performance throughout the semester?

Summary

This study sought to determine the moments where absenteeism becomes so problematic that student success intervention becomes necessary. Certainly, patterns emerged that help inform the practice of student success personnel and provide clear

evidence in support of attending class. This information proves useful for students as well, allowing them to see the impact of their behavior with the hopes of adjusting as necessary. The results of this study were not as strongly correlated as prior research (e.g., Crede, Roch, & Kieszczynka, 2010) and suggest other factors must also be considered to best inform the intervention of student success personnel. As a general principle however, the impact of absenteeism is largely detrimental to students' success. This message should not only be shared frequently with students, but also heavily emphasized with faculty. Their attitudes have a tremendous impact on student behavior. Although attendance is not a 'silver bullet' for student success, in and of itself, an attendance informed early-alert system may provide administrators with the opportunity to fulfill their missional objectives without increasing their budget, all while protecting academic freedom in the 'Age of Accountability.'

REFERENCES

- Abel, J., & Deitz, R. (2014). Do the benefits of college still outweigh the costs? *Current Issues in Economics and Finance*, 20(3), 1-12.
- Adelman, C. (2006). *The tool box revisited: Paths to degree completion from high school through college*. Washington, DC: U.S. Department of Education.
- Agresti, A. (2018). *An introduction to categorical data analysis*. New York, NY: Wiley.
- Arnold, K. E. (2010). Signals: Applying academic analytics. *Educause Quarterly*, 33(1)
- Bains, M., Reynolds, P. A., McDonald, F., & Sherriff, M. (2011). Effectiveness and acceptability of face-to-face, blended and e-learning: A randomised trial of orthodontic undergraduates. *European Journal of Dental Education*, 15(2), 110-117. <https://doi.org/10.1111/j.1600-0579.2010.00651.x>
- Barefoot, B. O. (2004). Higher education's revolving door: Confronting the problem of student drop out in US colleges and universities. *Open Learning: The Journal of Open, Distance and e-Learning*, 19(1), 9-18.
- Bell, B. S., & Federman, J. E. (2013). E-learning in postsecondary education. *The future of children*, 23(1), 165-185.
- Bishop, T. J., Martirosyan, N., Saxon, D. P., & Lane, F. (2018). Delivery method: Does it matter? A study of the North Carolina developmental mathematics redesign. *Community College Journal of Research and Practice*, 42(10), 712-723.
- Boylan, H. R. (2002). *What works: Research-based best practices in developmental education*. Continuous Quality Improvement Network with the National Center for Developmental Education, Appalachian State University.

- Brau, J. C., Young, B., Brau, R. I., Student, M., Psychology, I., Owen, S. R., ... Chain, S. (2016). The determinants of student performance in a university marketing class. *Business Education Innovation Journal*, 8(2), 21–32.
- Braun, K. W., & Drew Sellers, R. (2012). Using a “daily motivational quiz” to increase student preparation, attendance, and participation. *Issues in Accounting Education*, 27(1), 267–279. <https://doi.org/10.2308/iace-10219>
- Brown, S. D., Tramayne, S., Hoxha, D., Telander, K., Fan, X., & Lent, R. W. (2008). Social cognitive predictors of college students’ academic performance and persistence: A meta-analytic path analysis. *Journal of Vocational Behavior*, 72(3), 298-308.
- Campbell, D. T., & Stanley, J. C. (1966). *Experimental and quasi-experimental designs for research*. Chicago, IL: Rand McNally.
- Campbell, J. P., DeBlois, P. B., & Oblinger, D. G. (2007). Academic analytics: A new tool for a new era. *EDUCAUSE review*, 42(4), 40-57.
- Chen, J., & Lin, T.-F. (2008). Class attendance and exam performance: A randomized experiment. *The Journal of Economic Education*, 39(3), 213–227. <https://doi.org/10.3200/JECE.39.3.213-227>
- Chen, J., & Lin, T.-F. (2015). Effect of peer attendance on college students’ learning outcomes in a microeconomics course. *The Journal of Economic Education*, 46(4), 350–359. <https://doi.org/10.1080/00220485.2015.1071224>
- Choy, S. (2002). *Nontraditional undergraduates: Findings from the condition of education 2002* (NCES 2002-012). National Center for Education Statistics.

- Chung, C. J. (2004). The impact of attendance, instructor contact, and homework completion on achievement in a developmental logic course. *Research and Teaching in Developmental Education*, 20(2), 48-57.
- Collie, R. J., Martin, A. J., Malmberg, L. E., Hall, J., & Ginns, P. (2015). Academic buoyancy, student's achievement, and the linking role of control: A cross-lagged analysis of high school students. *The British Psychology Journal*, 85(1), 113-130.
- Concordia University Wisconsin. (2018). *Concordia University faculty handbook 2018-2019*. Retrieved from <https://falcon.cuw.edu/portal/FacHndbkCH125-6.pdf>
- Corbin, L., Burns, K., & Chrzanowski, A. (2010). If you teach it, will they come? Law students, class attendance and student engagement. *Legal Education Review*, 20(1-2), 13-44.
- Cotterill, S. S. (2015). Inspiring and motivating learners in higher education: The staff perspective. *Journal of Hospitality, Leisure, Sport & Tourism Education*, 17(2015), 5-13.
- Credé, M., & Kuncel, N. R. (2008). Study habits, skills, and attitudes: The third pillar supporting collegiate academic performance. *Perspectives on Psychological Science*, 3(6), 425-453.
- Crede, M., Roch, S. G., & Kieszczynka, U. M. (2010). Class attendance in college: A meta-analytic review of the relationship of class attendance with grades and student characteristics. *Review of Educational Research*, 80(2), 272-295.
<https://doi.org/10.3102/0034654310362998>
- Creswell, J. W. (2014). *Research design: Qualitative, quantitative, and mixed methods approaches*. Thousand Oaks, CA: Sage Publications.

- Crooks, A. D. (1933). Marks and marking systems: A digest. *Journal of Educational Research*, 27(4), 259-72.
- Dollinger, S. J., Matyja, A. M., & Huber, J. L. (2008). Which factors best account for academic success: Those which college students can control or those they cannot? *Journal of Research in Personality*, 42(4), 872-885.
- Dougherty, K. J., Jones, S. M., Lahr, H., Pheatt, L., Natow, R. S., & Reddy, V. (2016). *Performance funding for higher education*. Baltimore, MD: JHU Press.
- Druger, M. (2003). Being there. *Journal of College Science Teaching*, 32(5), 350-351.
- Ekowo, M., & Palmer, I. (2016). *The promise and peril of predictive analytics in higher education: A landscape analysis*. Washington, DC: New America
- Engle, J. (2007). Postsecondary access and success for first-generation college students. *American Academic*, 3(1), 25-48.
- Fjortoft, N. (2005). Students' motivations for class attendance. *American Journal of Pharmaceutical Education*, 69(1), 107-112. <https://doi.org/10.5688/aj690115>
- Friedman, P., Rodriguez, F., & McComb, J. (2001). Why students do and do not attend classes: Myths and realities. *College Teaching*, 49(4), 124-133.
- Gladieux, L. E. (1995). Federal student aid policy: A history and an assessment. In *Financing postsecondary education: The federal role*. Washington, DC: Department of Education. Retrieved from <https://files.eric.ed.gov/fulltext/ED400775.pdf#page=45>
- Groce, C., Willis, T., Sonner, B. S., & James, W. L. (2012). Mandatory Class Attendance Policies: Examining the Student Perspective. Proceedings of the Northeast Business & Economics Association. Gump, S. E. (2004a). Keep students coming

- by keeping students interested: Motivators for class attendance. *College Student Journal*, 38(1), 157-161.
- Gump, S. E. (2004b). The truth behind truancy: Student rationales for cutting class. *Educational Research Quarterly*, 28(2), 48-57.
- Gump, S. E. (2005). The cost of cutting class: Attendance as a predictor of success. *College Teaching*, 53(1), 21-26.
- Guy, G. M., Cornick, J., & Beckford, I. (2015). More than Math: On the affective domain in developmental mathematics. *International Journal for the Scholarship of Teaching & Learning*, 9(2), 1-5.
- Hall, B., & O'Neal, T. (2016). The Residential Learning Community as a Platform for High-Impact Educational Practices Aimed at At-Risk Student Success. *Journal of the Scholarship of Teaching and Learning*, 16(6), 42-55.
- Heffernan, J. M. (1973). The credibility of the credit hour: The history, use, and shortcomings of the credit system. *The Journal of Higher Education*, 44(1), 61-72.
- Higher Education Act of 1965, Section 484B, 34 CFR 668.22 (2018).
- Hillman, N. W., Tandberg, D. A., & Fryar, A. H. (2015). Evaluating the impacts of “new” performance funding in higher education. *Educational Evaluation and Policy Analysis*, 37(4), 501-519.
- Howard, T. C. (2010). *Why race and culture matter in schools: Closing the achievement gap in America's classrooms* (Vol. 39). New York, NY: Teachers College Press.

- Hudson Sr, W. E. (2005). Can an early alert excessive absenteeism warning system be effective in retaining freshman students? *Journal of College Student Retention: Research, Theory & Practice*, 7(3), 217-226.
- Hutt, E. (2016). A brief history of the student record. Retrieved from https://sr.ithaka.org/wp-content/uploads/2016/09/SR_Report_Hutt_Brief_History_Student_Record_090616.pdf
- Islam, M. N., Salam, A., Bhuiyan, M., & Daud, S. B. (2018). A Comparative Study on Achievement of Learning Outcomes through Flipped Classroom and Traditional Lecture Instructions. *International Medical Journal*, 25(5), 314-317.
- Jayaprakash, S. M., Moody, E. W., Lauría, E. J., Regan, J. R., & Baron, J. D. (2014). Early alert of academically at-risk students: An open source analytics initiative. *Journal of Learning Analytics*, 1(1), 6-47.
- Johnson, S. D., Aragon, S. R., Shaik, N., & Palma-Rivas, N. (1999). *Comparative analysis of online vs. face-to-face instruction*. Retrieved from <https://files.eric.ed.gov/fulltext/ED448722.pdf>
- Jones, E. R. (1999). *A comparison of an all web-based class to a traditional class*. Retrieved from <https://files.eric.ed.gov/fulltext/ED432286.pdf>
- Jurgens, J. C. (2010). The evolution of community colleges. *College Student Affairs Journal*, 28(2), 251.
- Kohn, A. (2011). The case against grades. *Educational Leadership*, 69(3), 28-33.

- Küçük, S., Kapakin, S., & Göktaş, Y. (2016). Learning anatomy via mobile augmented reality: effects on achievement and cognitive load. *Anatomical sciences education*, 9(5), 411-421.
- Kulik, J., Kulik, C-L., & Schwalb, B. (1983). College programs for high risk and disadvantaged students: A meta-analysis of findings. *Review of Educational Research*, 53(3), 397-414.
- Leary, K. A., & DeRosier, M. E. (2012). Factors promoting positive adaptation and resilience during the transition to college. *Psychology*, 3(12), 1215-1222.
- Liebler, R. J. 2003. The five-minute quiz. *Journal of Accounting Education* 21(3), 261–265.
- Lin, T. C. (2014). Does missing classes decelerate student exam performance progress? Empirical evidence and policy implications. *Journal of Education for Business*, 89(8), 411–418. <https://doi.org/10.1080/08832323.2014.927343>
- Lin, T. F., & Chen, J. (2006). Cumulative class attendance and exam performance. *Applied Economics Letters*, 13(14), 937–942. <https://doi.org/10.1080/13504850500425733>
- Lonn, S., Aguilar, S. J., & Teasley, S. D. (2015). Investigating student motivation in the context of a learning analytics intervention during a summer bridge program. *Computers in Human Behavior*, 47, 90-97. doi:10.1016/j.chb.2014.07.013
- Lowry, R. (2019). *Significance of the difference between two correlation coefficients*. Retrieved from <http://vassarstats.net/rdiff.html>

- Lukkarinen, A., Koivukangas, P., & Seppälä, T. (2016). Relationship between class attendance and student performance. *Procedia - Social and Behavioral Sciences*, 228(2016), 341–347. <https://doi.org/10.1016/j.sbspro.2016.07.051>
- Miao, K. (2012). *Performance-based funding of higher education: A detailed look at best practices in 6 states*. Washington, DC: Center for American Progress.
- Marburger, D. R. (2001). Absenteeism and undergraduate exam performance. *The Journal of Economic Education*, 32(2), 99-109.
- Macfarlane, B. (2013). The surveillance of learning: A critical analysis of university attendance policies. *Higher Education Quarterly*, 67(4), 358-373.
- Moore, R. (2003). Students' choices in developmental education: Is it really important to attend class? *Research and Teaching in Developmental Education*, 20(1) 42-52.
- Moore, R. (2005). Attendance: Are penalties more effective than rewards? *Journal of Developmental Education*, 29(2), 26–32.
- Moore, R. (2006). Class attendance: How students attitudes about attendance relate to their academic performance in introductory science classes. *Research & Teaching in Developmental Education*, 23(1), 19–33.
- Moore, S., Armstrong, C., & Pearson, J. (2008). Lecture absenteeism among students in higher education: A valuable route to understanding student motivation. *Journal of Higher Education Policy and Management*, 30(1), 15–24.
<https://doi.org/10.1080/13600800701457848>
- Moore, R., & Jensen, P. A. (2008). Do policies that encourage better attendance in lab change students' academic behaviors and performances in introductory science courses? *Science Educator*, 17(1), 64-71.

- Morales, E. E. (2010). Linking strengths: Identifying and exploring protective factor clusters in academically resilient low-socioeconomic urban students of color. *Roeper Review*, 32(3), 164-175.
- National Center for Educational Statistics. (2018). *Undergraduate retention and graduation rates*. Retrieved from https://nces.ed.gov/programs/coe/indicator_ctr.asp
- National Research Council. (1995). *Colleges of agriculture at the land grant universities: A profile*. Washington, DC: National Academies Press
- Newman-Ford, L., Fitzgibbon, K., Lloyd, S., & Thomas, S. (2008). A large-scale investigation into the relationship between attendance and attainment: A study using an innovative, electronic attendance monitoring system. *Studies in Higher Education*, 33(6), 699–717. <https://doi.org/10.1080/03075070802457066>
- Onwuegbuzie, A. J. (2000). Expanding the framework of internal and external validity in quantitative research. *Research in the Schools*, 10(1), 71-90.
- Onwuegbuzie, A. J., Bailey, P., & Daley, C. E. (2000). Cognitive, affective, personality, and demographic predictors of foreign-language achievement. *The Journal of Educational Research*, 94(1), 3-15.
- Pascarella, E. T., Pierson, C. T., Wolniak, G. C., & Terenzini, P. T. (2004). First-generation college students: Additional evidence on college experiences and outcomes. *The Journal of Higher Education*, 75(3), 249-284.
- Perna, L. W., & Thomas, S. L. (2006). A framework for reducing the college success gap and promoting success for all. *National Symposium on Postsecondary Student*

- Success: Spearheading a Dialog on Student Success*. Retrieved from https://repository.upenn.edu/gse_pubs/328
- Rais-Rohani, M., & Walters, A. (2014). Preliminary assessment of the Emporium Model in a redesigned engineering mechanics course. *Advances in Engineering Education*, 4(1).
- Reardon, S. F. (2013). The widening income achievement gap. *Educational Leadership*, 70(8), 10-16.
- Robbins, S. B., Lauver, K., Le, H., Davis, D., & Langley, R. (2004). Do psychosocial and study skill factors predict college outcomes? A meta-analysis. *Psychological Bulletin*, 130(2), 261–288.
- Rubel, A., & Jones, K. M. (2016). Student privacy in learning analytics: An information ethics perspective. *The Information Society*, 32(2), 143-159.
- Schmitt, N., Keeney, J., Oswald, F. L., Pleskac, T. J., Billington, A. Q., Sinha, R., & Zorzie, M. (2009). Prediction of 4-year college student performance using cognitive and noncognitive predictors and the impact on demographic status of admitted students. *Journal of Applied Psychology*, 94(6), 1479-1497.
- Shimoff, E., & Catania, A. C. (2001). Effects of recording attendance on grades in introductory psychology. *Teaching of Psychology*, 28(3), 192–195.
https://doi.org/10.1207/S15328023TOP2803_04
- Snyder, J. L., Lee-Partridge, J. E., Jarmoszko, A. T., Petkova, O., & D’Onofrio, M. J. (2014). What is the influence of a compulsory attendance policy on absenteeism and performance? *Journal of Education for Business*, 89(8), 433–440.
<https://doi.org/10.1080/08832323.2014.933155>

- St. Clair, K. L. (1999). A case against compulsory class attendance policies in higher education. *Innovative Higher Education*, 23(3), 171-180.
- Sperber, M. (2005). Notes from a career in teaching. *The Chronicle of Higher Education*, 52(3), B20.
- Stoltzfus, J. C. (2011). Logistic regression: a brief primer. *Academic Emergency Medicine*, 18(10), 1099-1104.
- Taglieri, C., Schnee, D., Camiel, L. D., Zaiken, K., Mistry, A., Nigro, S., ... & Goldman, J. (2017). Comparison of long-term knowledge retention in lecture-based versus flipped team-based learning course delivery. *Currents in Pharmacy Teaching and Learning*, 9(3), 391-397.
- Thaler, R. H., & Sunstein, C. R. (2003). Libertarian paternalism. *American economic review*, 93(2), 175-179.
- Thelin, J. R. (2011). *A history of American higher education*. Baltimore, MD: JHU Press.
- Tinto, V. (1987). *Leaving college: Rethinking the causes and cures of student attrition*. Chicago, IL: University of Chicago Press .
- Tinto, V. (2005). *College student retention: Formula for student success*. Westport, CT: Greenwood Publishing Group.
- Tiruneh, G. (2007). Does attendance enhance political science grades? *Journal of Political Science Education*, 3(3), 265–276.
<https://doi.org/10.1080/15512160701620776>
- Turner, M., Scott-Young, C. M., & Holdsworth, S. (2016). Bouncing back to move forward: Resilience of students in the built environment. In *Association of Researchers in Construction Management*, 1, 589-598.

- Twigg, C. A. (2011). The math emporium: Higher education's silver bullet. *Change: The Magazine of Higher Learning*, 43(3), 25-34.
- Varao-Sousa, T. L., & Kingstone, A. (2015). Memory for lectures: How lecture format impacts the learning experience. *PloS one*, 10(11), e0141587.
- Wilkinson, L. (1999). Statistical methods in psychology journals: Guidelines and explanations. *American psychologist*, 54(8), 594.
- Williams, A. E., Aguilar-Roca, N. M., & O'Dowd, D. K. (2016). Lecture capture podcasts: Differential student use and performance in a large introductory course. *Educational Technology Research and Development*, 64(1), 1-12.
- Yorke, M., & Longden, B. (2004). *Retention and student success in higher education*. UK: McGraw-Hill Education.
- Zhang, D., Zhao, J. L., Zhou, L., & Nunamaker Jr, J. F. (2004). Can e-learning replace classroom learning?. *Communications of the ACM*, 47(5), 75-79.
- Zilvinskis, J., Masseria, A. A., & Pike, G. R. (2017). Student engagement and student learning: examining the convergent and discriminant validity of the revised national survey of student engagement. *Research in Higher Education*, 58(8), 880-903.

APPENDIX



Date: May 7, 2019 10:49 AM CDT

TO: Andrew Miller

Susana Skidmore

FROM: SHSU IRB

PROJECT TITLE: Examining the Efficacy of Attendance as a Predictor of Academic Performance

PROTOCOL #: IRB-2019-140

SUBMISSION TYPE: Initial

ACTION: Exempt

DECISION DATE: May 7, 2019

EXEMPT REVIEW CATEGORY: Category 4. Secondary research for which consent is not required: Secondary research uses of identifiable private information or identifiable biospecimens, if at least one of the following criteria is met:

- (i) The identifiable private information or identifiable biospecimens are publicly available;
- (ii) Information, which may include information about biospecimens, is recorded by the investigator in such a manner that the identity of the human subjects cannot readily be ascertained directly or through identifiers linked to the subjects, the investigator does not contact the subjects, and the investigator will not re-identify subjects;
- (iii) The research involves only information collection and analysis involving the investigator's use of identifiable health information when that use is regulated under 45 CFR parts 160 and 164, subparts A and E, for the purposes of "health care operations" or "research" as those terms are defined at 45 CFR 164.501 or for "public health activities and purposes" as described under 45 CFR 164.512(b); or
- (iv) The research is conducted by, or on behalf of, a Federal department or agency using government-generated or government-collected information obtained for nonresearch activities, if the research generates identifiable private information that is or will be maintained on information technology that is subject to and in compliance with section 208(b) of the E-Government Act of 2002, 44 U.S.C. 3501 note, if all of the identifiable private information collected, used, or generated as part of the activity will be maintained in systems of records subject to the Privacy Act of 1974, 5 U.S.C. 552a, and, if applicable, the information used in the research was collected subject to the Paperwork Reduction Act of 1995, 44 U.S.C. 3501 et seq.

Greetings,

Thank you for your submission of Initial Review materials for this project. The Sam Houston State University (SHSU) IRB has determined this project is EXEMPT FROM IRB REVIEW according to federal regulations.

Since Cayuse IRB does not currently possess the ability to provide a "stamp of approval" on any recruitment or consent documentation, it is the strong recommendation of this office to please include the following approval language in the footer of those recruitment and consent documents: IRB-2019-140/May 7, 2019.

We will retain a copy of this correspondence within our records.

*** What should Investigators do when considering changes to an exempt study that could make it nonexempt?**

It is the PI's responsibility to consult with the IRB whenever questions arise about whether planned changes to an exempt study might make that study nonexempt human subjects research.

In this case, please make available sufficient information to the IRB so it can make a correct determination.

If you have any questions, please contact the IRB Office at 936-294-4875 or irb@shsu.edu. Please include your project title and protocol number in all correspondence with this committee.

Sincerely,

Donna M. Desforges, Ph.D.
Chair, Committee for the Protection of Human Subjects
PHSC-IRB

VITA

ANDREW P MILLER

SUMMARY

Conscientious higher education reformer who can communicate with both technical and functional units to leverage data analytics and collaboratively solve complex problems in higher education. Myriad roles throughout my nine years in academic and student affairs afford me a robust understanding of the diverse perspectives intertwined to create cultures of student success.

SKILLS & EXPERTISE

Data translator
Innovative troubleshooter
Cross-functional collaborator
SQL, Python, & R
Student-success & retention
Student-success analytics
Enrollment Management
Non-cognitive student development

PROFESSIONAL EXPERIENCE

Director – Center for Academic Advising & Career Engagement | Concordia University Wisconsin 2018-Present

Designed and implemented the restructure of the Academic Advising office and Career Services. Rebuilt university-, unit-, and staff-level expectations and accountability metrics to enhance student-success cultures across campus.

- Communicated functional specifications to technical consultants to deploy customized solutions of our analytics advising platform across the institution (including Banner, Degree Works, Blackboard, and Aviso systems)
- Partnered with senior administrators to scale a redesigned advising model across the institution, contributing to a 11% increase in 4-year graduation rates
- Created a series of custom analytics reports for faculty and staff to inform just-in-time student support
- Designed a holistic faculty advising training module and assessment plan, increasing faculty engagement and compliance with University policies to as much as 95%

Director of Academic Advising & Retention | Concordia University Wisconsin 2017-2018

Elevated role of academic advising by purposefully partnering with senior level administrators and communicating a researched informed narrative for strategically placing advising at the frontlines of the student experience.

- Constructed, coordinated, and evaluated an analytics-informed early alert system to connect students who are in academic jeopardy with the appropriate support systems – resulted in 10% increase in retention

- Analyzed retention and attrition data to identify trends and potential solutions, produced reports based on thorough data analysis and collaborated with stakeholders to implement changes for effective programming
- Garnered capital funding and managed the expansion of our advising platform to an enterprise system
- Redesigned Summer Orientation for incoming students, reducing new student enrollment *melt* from 12% to 4%

Academic Advisor & PROSPER Coordinator | Concordia University Wisconsin
2015-2017

Built a cross-campus coalition of student-success professionals for academic coaching programs designed to help underprepared and academically at-risk students.

- Designed two academic coaching programs where engaged students earned GPAs .66 higher than control group
- Created personalized analytics dashboards for each professional academic advisor using Blackboard Intelligence
- Automated the process of disseminating and socializing a series of analytics reports for faculty advisors
- Advised a caseload of 125 Pre-Nursing students for academic planning and academic success

Transfer Admission Counselor | Concordia University Wisconsin 2013-2015

Established partnerships with area technical colleges to foster recruitment pipelines within Southeastern Wisconsin.

- Created Ellucian CRM administered marketing campaigns to attract talented students from diverse pool of leads
- Secured *Preferred Partnership* with area technical college, manifesting in 12 program articulation agreements
- Recruited 100 transfer students through to matriculation during the 2014 application term

EDUCATION

Sam Houston State University 2016-Present

Doctor of Education – Developmental Education Administration

Cohort 5 – anticipated graduation 2019

Dissertation (in progress): Examining the Efficacy of Attendance as a Predictor of Academic Performance

Concordia University Wisconsin September 2013

Master of Science – Student Personnel Administration – Athletic Administration

Thesis: Academic, Athletic, and Career Motivation as Predictors of Academic Success in Student-Athletes at an NCAA Division III Institution

University of Minnesota, Twin Cities December 2009
Bachelor of Arts - Political Science

COMMITTEE INVOLVEMENT

Momentum Pathways Action Summit – Complete College America
2019-Present
EDUCAUSE – Student Success Analytics Constituent Group – Steering
Committee 2018-Present
National Organization for Student Success – Guided Pathways & Advising
Network Co-chair 2017-Present
Strategic Information Analysis Council –
Concordia University Wisconsin 2015-Present
Data Governance Committee – SIAC – *Concordia University Wisconsin*
2017-Present
Pyramid Report Administrative Committee – *Concordia University Wisconsin*
2017-Present
Pastoral Council – Executive Committee – *St. Alphonsus, Greendale, WI*
2015-2018
Admission Review Committee – *Concordia University Wisconsin* 2015-2016
Retention Think Tank – *Concordia University Wisconsin* 2013-2015

AWARDS

Blackboard Catalyst Award for Optimizing the Student Experience
2018
Raven's Scholars Award – Sam Houston State University
2018
National Academic Advising Association – Research Grant
2016-2018

PROFESSIONAL CONTRIBUTIONS

Miller, A. P. (2018). *Engaging students FAST: Out of the box*. Presented at the Blackboard Analytics Symposium, Austin, TX.

Brandt, C., & Miller, A. P. (2018). *Advising the advisors!* Presented at the Blackboard Analytics Symposium, Austin, TX.

Miller, A. P. (2018). *Faith, hope, and love: How beliefs shape academic resilience*. Presented at the National Association of Developmental Education Conference, National Harbor, MD.

Polzin, E., & Miller, A. P. (2017). *More than just a number: Maintaining a student-centric approach while taking the data plunge*. Presented at the National Academic Advising Association Conference, St. Louis, MO.

- Lane, F. C., & Miller, A. P. (2017). *First-year experience seminars: A benchmark study of targeted courses for developmental education students*. Presented at the National Association of Developmental Education Conference, Oklahoma City, OK.
- Miller, A. P. (2017). *Students: Just a number? Integrating data to game plan for student success*. Presented at Wisconsin Academic Advising Association Conference, Oshkosh, WI.
- Miller, A. P. (2016, November). *An academic coaching model for first-year student success*. Paper presented at National Symposium on Student Retention, Norfolk, VA.
- Miller, A. P. (2016, November). *An academic coaching model for first-year student success*. Poster presentation at National Symposium on Student Retention, Norfolk, VA.
- Miller, A. P. (2016, September). *An academic coaching model for first-year student success*. Paper presented at Wisconsin Academic Advising Association Conference, Green Bay, WI.
- Miller, A. P. (2012). *Academic, athletic, and career motivation as predictors of academic success in student-athletes at an NCAA Division III institution*. (Unpublished master's thesis). Concordia University Wisconsin, Mequon, WI.
- Miller, A.P. (2014, December). *The 'Right' Fit*. Retrieved from URL: <http://www.nacacnet.org/research/transfer/KeystoSuccess/Pages/TheRightFit.aspx>